Algorithm Optimizer: Product Requirements Document (PRD)

Version: 1.0

Date: January 2025

Document Owner: Chief Data Scientist

Stakeholders: Engineering, Data Science, DevOps, Executive Leadership

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1. Executive Summary

1.1 Product Vision

Develop an AI-powered system that automatically optimizes any algorithm's performance using reinforcement learning, delivering significant speed improvements and cost savings while maintaining algorithmic correctness.

1.2 Business Objectives

- **Primary Goal:** Reduce ML pipeline execution time by 5-45× through automated algorithm optimization
- **Secondary Goals:**
  - Cut cloud computing costs by 70-95%
  - Increase data scientist productivity by 20-25%
  - Improve model quality through better feature selection and hyperparameter tuning

1.3 Success Metrics

- **Performance:** Achieve 5× minimum speedup on 90% of optimized algorithms
- **Adoption:** 80% of data science teams using the platform within 6 months
- **ROI:** 13× return on investment within first year
- **Reliability:** 99.5% uptime with <1% optimization failure rate

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2. Problem Statement

2.1 Current Challenges

- **Manual Optimization:** Algorithm tuning requires specialized expertise and weeks of manual effort
- **Sub-optimal Performance:** Most algorithms run with default parameters, missing significant performance gains

- **High Compute Costs:** Inefficient algorithms consume excessive cloud resources
- **Time-to-Market Delays:** Slow algorithms bottleneck model development and deployment

2.2 Market Opportunity

- **Total Addressable Market:** $2.8B in global cloud computing costs for ML workloads
- **Immediate Opportunity:** $12M annual savings potential within our organization
- **Competitive Advantage:** First-to-market with general-purpose algorithm optimization platform

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3. Product Overview

3.1 Product Description

A cloud-native platform that uses reinforcement learning to automatically optimize algorithm performance through parameter tuning and execution strategy improvements, deployed on Kubernetes with Kubeflow orchestration.

3.2 Core Value Propositions

1. **Automated Optimization:** Zero-effort algorithm improvement without manual tuning
2. **Universal Compatibility:** Works with any algorithm type (sorting, ML, optimization, etc.)
3. **Production-Ready:** Seamless integration with existing ML pipelines
4. **Measurable Impact:** Quantifiable performance and cost improvements

3.3 Target Users

- **Primary:** Data Scientists and ML Engineers
- **Secondary:** DevOps Engineers, Software Developers
- **Stakeholders:** Engineering Leadership, Finance Teams

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4. Functional Requirements

4.1 Core Features

4.1.1 Algorithm Analysis Engine

Priority: P0 (Must Have)

Description: Automatically analyze algorithms to identify optimization opportunities

Requirements:

- Parse algorithm source code to identify parameters
- Generate parameter space configuration automatically
- Create execution wrappers with performance monitoring
- Support Python, R, and Scala algorithms initially

Acceptance Criteria:

- Successfully analyze 95% of submitted algorithms
- Identify all tunable parameters within 30 seconds
- Generate valid parameter ranges for continuous and discrete parameters
- Create execution wrappers that capture performance metrics

4.1.2 Test Case Generation

Priority: P0 (Must Have)

Description: Generate diverse test cases for algorithm evaluation

Requirements:

- Create test datasets based on algorithm type (sorting, ML, optimization)
- Generate difficulty levels from simple to complex
- Support multiple data types (int, float, mixed, categorical)
- Maintain test case versioning and reproducibility

Acceptance Criteria:

- Generate 800+ test cases per algorithm type
- Cover 5 difficulty levels with appropriate distribution
- Ensure reproducible test case generation
- Support custom test case injection

4.1.3 Reinforcement Learning Optimization Engine

Priority: P0 (Must Have)

Description: Train RL agents to optimize algorithm parameters

Requirements:

- Implement Group Relative Policy Optimization (GRPO)

- Support distributed training across multiple nodes
- Provide real-time training progress monitoring
- Enable early stopping and checkpoint management

Acceptance Criteria:

- Train RL agents that achieve 5× minimum speedup on 90% of test cases
- Complete training within 2 hours for typical algorithms
- Support parallel training on 4-16 nodes
- Maintain training state through interruptions

4.1.4 Performance Evaluation Framework

Priority: P0 (Must Have)

Description: Measure and compare algorithm performance

Requirements:

- Capture execution time, memory usage, CPU utilization
- Ensure correctness verification for all optimizations
- Provide statistical significance testing
- Generate performance comparison reports

Acceptance Criteria:

- Measure performance with <5% variance across runs
- Verify 100% correctness of optimized algorithms
- Provide confidence intervals for performance improvements
- Generate automated performance reports

4.1.5 Deployment Management

Priority: P0 (Must Have)

Description: Deploy optimized algorithms to production

Requirements:

- Package optimized algorithms as container images
- Deploy to Kubernetes with auto-scaling

- Provide REST API for algorithm execution
- Support A/B testing between baseline and optimized versions

Acceptance Criteria:

- Deploy optimized algorithms within 5 minutes
- Support 1000+ concurrent requests per algorithm
- Provide 99.9% uptime for deployed algorithms
- Enable seamless rollback to baseline versions

4.2 Advanced Features

4.2.1 Multi-Algorithm Optimization

Priority: P1 (Should Have)

Description: Optimize entire algorithm pipelines

Requirements:

- Optimize sequences of connected algorithms
- Balance trade-offs between different optimization objectives
- Support pipeline-level performance metrics

4.2.2 Transfer Learning

Priority: P1 (Should Have)

Description: Apply optimizations across similar algorithms

Requirements:

- Identify similar algorithms for knowledge transfer
- Reduce optimization time for similar algorithm types
- Maintain optimization knowledge base

4.2.3 Real-time Adaptation

Priority: P2 (Nice to Have)

Description: Adapt algorithm parameters based on runtime conditions

Requirements:

- Monitor runtime performance and data characteristics
- Dynamically adjust parameters based on workload
- Provide feedback loop for continuous improvement

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5. Non-Functional Requirements

5.1 Performance Requirements

- **Training Time:** Complete RL optimization within 2 hours for typical algorithms
- **Inference Time:** Execute optimized algorithms with <10ms additional overhead
- **Throughput:** Support 1000+ concurrent algorithm executions
- **Scalability:** Scale to 100+ algorithms and 10,000+ test cases

5.2 Reliability Requirements

- **Uptime:** 99.5% availability for core services
- **Data Durability:** 99.999% durability for optimization models and results
- **Fault Tolerance:** Automatic recovery from node failures
- **Backup & Recovery:** Complete system recovery within 4 hours

5.3 Security Requirements

- **Authentication:** Integration with corporate SSO
- **Authorization:** Role-based access control (RBAC)
- **Data Protection:** Encryption at rest and in transit
- **Audit Logging:** Complete audit trail of all optimization activities

5.4 Usability Requirements

- **Learning Curve:** New users productive within 1 hour
- **API Response Time:** <200ms for synchronous operations
- **Documentation:** Comprehensive API docs and user guides
- **Error Handling:** Clear error messages and troubleshooting guidance

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6. Technical Architecture

6.1 High-Level Architecture

```
┌──────────────────────┐   ┌──────────────────────┐
┌──────────────────────┐
│  Web UI      │  │  REST API     │  │  CLI Tool     │
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   │            │            │

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│             API Gateway                    │
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│Algorithm      │   │RL Training     │   │Deployment     │
│Analysis       │   │Service         │   │Manager        │
│Service        │   │                │   │               │
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┌──────────────────────┐
│Test Case      │   │Performance     │   │Model          │
│Generator      │   │Evaluator       │   │Registry       │
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│          Infrastructure Layer                    │
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┌──────────────┐ │
│ │Kubernetes │ │Kubeflow  │ │PostgreSQL │ │Redis   ││
│ │(EKS)      │ │Pipelines │ │           │ │        ││
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```

6.2 Technology Stack

6.2.1 Infrastructure

- **Container Orchestration:** Amazon EKS (Kubernetes)
- **ML Workflows:** Kubeflow Pipelines 2.0
- **Service Mesh:** Istio for inter-service communication
- **Monitoring:** Prometheus + Grafana
- **Logging:** ELK Stack (Elasticsearch, Logstash, Kibana)

6.2.2 Backend Services

- **API Framework:** FastAPI with async support
- **RL Framework:** Ray RLlib with custom GRPO implementation
- **ML Libraries:** TensorFlow, PyTorch, Scikit-learn
- **Database:** PostgreSQL for metadata, Redis for caching
- **Message Queue:** Apache Kafka for async processing

6.2.3 Frontend & Integration

- **Web UI:** React.js with TypeScript
- **Visualization:** D3.js, Plotly.js for charts
- **CLI Tool:** Python Click framework
- **API Documentation:** OpenAPI/Swagger

6.3 Data Architecture

6.3.1 Data Models

```sql
```

```
-- Algorithms
algorithms (
  id UUID PRIMARY KEY,
  name VARCHAR(255),
  source_code TEXT,
  algorithm_type VARCHAR(100),
  parameter_config JSONB,
  created_at TIMESTAMP,
  updated_at TIMESTAMP
)

-- Test Cases
test_cases (
  id UUID PRIMARY KEY,
  algorithm_id UUID REFERENCES algorithms(id),
  data JSONB,
  metadata JSONB,
  difficulty INTEGER,
  created_at TIMESTAMP
)

-- Optimization Runs
optimization_runs (
  id UUID PRIMARY KEY,
  algorithm_id UUID REFERENCES algorithms(id),
  status VARCHAR(50),
  hyperparameters JSONB,
  metrics JSONB,
  model_path VARCHAR(500),
  started_at TIMESTAMP,
  completed_at TIMESTAMP
)

-- Performance Results
performance_results (
  id UUID PRIMARY KEY,
  optimization_run_id UUID REFERENCES optimization_runs(id),
  test_case_id UUID REFERENCES test_cases(id),
  baseline_metrics JSONB,
  optimized_metrics JSONB,
  speedup_ratio DECIMAL(10,2),
  is_correct BOOLEAN,
```

```
    created_at TIMESTAMP
)
```

6.3.2 Data Flow

1. **Algorithm Ingestion:** Source code → Analysis Service → Parameter extraction
2. **Test Generation:** Algorithm type → Test Case Generator → Diverse test datasets
3. **RL Training:** Test cases + Algorithm → RL Training Service → Optimized model
4. **Evaluation:** Optimized model + Test cases → Performance Evaluator → Results
5. **Deployment:** Optimized model → Deployment Manager → Production service

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7. User Experience Design

7.1 User Journeys

7.1.1 Data Scientist - Algorithm Optimization

1. **Upload Algorithm:** Drag-and-drop Python file or paste code
2. **Configure Parameters:** Review auto-detected parameters, adjust ranges
3. **Start Optimization:** Select optimization targets and start training
4. **Monitor Progress:** Real-time dashboard showing training progress
5. **Review Results:** Performance comparison, speedup metrics, recommendations
6. **Deploy Optimized:** One-click deployment to production

7.1.2 DevOps Engineer - Production Management

1. **Monitor Performance:** Dashboard showing all deployed algorithms
2. **Scale Services:** Auto-scaling configuration and manual overrides
3. **Manage Versions:** A/B testing and rollback capabilities
4. **Review Costs:** Cost analysis and optimization recommendations

7.2 User Interface Requirements

7.2.1 Main Dashboard

- **Algorithm Overview:** List of all algorithms with status indicators
- **Performance Metrics:** Real-time performance charts and KPIs
- **Resource Usage:** Compute utilization and cost tracking

- **Recent Activity:** Latest optimizations and deployments

7.2.2 Algorithm Detail Page

- **Source Code Viewer:** Syntax-highlighted code with annotations
- **Parameter Configuration:** Interactive parameter tuning interface
- **Optimization History:** Timeline of optimization attempts
- **Performance Comparison:** Before/after performance visualizations

7.2.3 Training Progress Page

- **Real-time Charts:** Training loss, reward, and performance metrics
- **Resource Monitoring:** CPU, memory, and GPU utilization
- **Log Viewer:** Real-time training logs with filtering
- **Control Panel:** Stop, pause, and restart training operations

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8. Integration Requirements

8.1 External Integrations

8.1.1 Version Control Systems

- **GitHub/GitLab Integration:** Direct algorithm import from repositories
- **Automated Optimization:** Trigger optimization on code commits
- **Results Publishing:** Commit optimization results back to repositories

8.1.2 CI/CD Pipelines

- **Jenkins/GitHub Actions:** Integration with existing pipelines
- **Automated Testing:** Run optimization validation in CI
- **Deployment Automation:** Automatic deployment of optimized algorithms

8.1.3 Monitoring & Observability

- **DataDog/New Relic:** Integration with existing monitoring
- **Alert Management:** Custom alerts for optimization failures
- **Performance Tracking:** Long-term performance trend analysis

8.2 Internal Integrations

8.2.1 Data Platform

- **Data Lake Integration:** Access to training datasets
- **Feature Store:** Integration with feature management systems
- **Metadata Management:** Sync with data catalog systems

8.2.2 ML Platform

- **MLflow Integration:** Model versioning and registry
- **Experiment Tracking:** Integration with existing experiment systems
- **Model Serving:** Integration with model serving infrastructure

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9. Implementation Plan

9.1 Phase 1: Foundation (Days 1-30)

Objective: Establish core infrastructure and basic optimization capability

Deliverables:

- [ ] EKS cluster setup with Kubeflow Pipelines
- [ ] Algorithm Analysis Service (MVP)
- [ ] Test Case Generator (basic functionality)
- [ ] RL Training Service (GRPO implementation)
- [ ] Performance Evaluation Framework
- [ ] Basic Web UI for algorithm submission

Success Criteria:

- Successfully optimize a simple sorting algorithm
- Demonstrate 5× minimum speedup on test cases
- Deploy optimized algorithm to Kubernetes

Resources:

- 2 Backend Engineers
- 1 ML Engineer
- 1 DevOps Engineer

9.2 Phase 2: ML Algorithm Focus (Days 31-60)

Objective: Specialize in ML algorithm optimization with production features

Deliverables:

- [ ] Feature Selection optimization (RFE, SelectKBest)
- [ ] Hyperparameter tuning optimization (GridSearch, RandomSearch)
- [ ] Advanced UI with training progress monitoring
- [ ] REST API with comprehensive documentation
- [ ] A/B testing framework
- [ ] Basic monitoring and alerting

Success Criteria:

- Optimize 5 different ML algorithms successfully
- Achieve 10× average speedup on feature selection
- Deploy production-ready API with 99% uptime

Resources:

- 3 Backend Engineers
- 2 ML Engineers
- 1 Frontend Engineer
- 1 DevOps Engineer

9.3 Phase 3: Enterprise Features (Days 61-90)

Objective: Add enterprise-grade features for organization-wide adoption

Deliverables:

- [ ] Self-service portal with role-based access
- [ ] CLI tool for developer integration
- [ ] Transfer learning between algorithms
- [ ] Multi-objective optimization
- [ ] Comprehensive monitoring dashboard
- [ ] Documentation and training materials

Success Criteria:

- 80% of data science teams actively using the platform
- Demonstrate 13× ROI through cost savings
- Complete security audit and compliance review

Resources:

- 4 Backend Engineers
- 2 ML Engineers
- 2 Frontend Engineers
- 1 DevOps Engineer
- 1 Technical Writer

9.4 Post-Launch: Optimization & Scaling (Days 91+)

Objective: Continuous improvement and advanced features

Focus Areas:

- Real-time algorithm adaptation
- Multi-cloud deployment support
- Advanced visualization and analytics
- Integration with additional ML frameworks
- Performance optimization and cost reduction

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10. Success Metrics & KPIs

10.1 Product Metrics

10.1.1 Performance Metrics

- **Primary KPI:** Average algorithm speedup ratio (Target: 10×)
- **Optimization Success Rate:** Percentage of algorithms improved (Target: 90%)
- **Training Time:** Average time to complete optimization (Target: <2 hours)
- **Accuracy Preservation:** Algorithms maintaining correctness (Target: 100%)

10.1.2 Business Metrics

- **Cost Savings:** Monthly cloud computing cost reduction (Target: $250K/month)
- **Productivity Gain:** Data scientist time saved per week (Target: 8 hours/person)
- **ROI:** Return on investment (Target: 13× in first year)
- **Time-to-Market:** Model development cycle reduction (Target: 30%)

10.1.3 Adoption Metrics

- **Active Users:** Monthly active users (Target: 100+ within 6 months)
- **Algorithm Coverage:** Number of optimized algorithms (Target: 50+ within 6 months)
- **API Usage:** Daily API calls (Target: 10,000+ within 6 months)
- **User Satisfaction:** NPS score (Target: >70)

10.2 Technical Metrics

10.2.1 System Performance

- **Uptime:** System availability (Target: 99.5%)
- **Response Time:** API response time P95 (Target: <200ms)
- **Throughput:** Concurrent optimization capacity (Target: 100 algorithms)
- **Resource Utilization:** Cluster CPU/memory efficiency (Target: >70%)

10.2.2 Quality Metrics

- **Bug Rate:** Production bugs per release (Target: <5)
- **Test Coverage:** Code test coverage (Target: >80%)
- **Security Score:** Security assessment score (Target: A grade)
- **Documentation Coverage:** API documentation completeness (Target: 100%)

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11. Risk Assessment & Mitigation

11.1 Technical Risks

11.1.1 RL Training Convergence

Risk: RL agents may not converge to optimal solutions **Probability:** Medium **Impact:** High **Mitigation:**

- Implement multiple RL algorithms (PPO, SAC) as fallbacks
- Use warm-start strategies with classical optimization
- Extensive hyperparameter tuning and early stopping

11.1.2 Correctness Verification

Risk: Optimized algorithms may produce incorrect results **Probability:** Low **Impact:** Critical **Mitigation:**

- Comprehensive correctness testing framework
- Statistical validation of results

- Gradual rollout with extensive monitoring

11.1.3 Scalability Limitations

Risk: System may not scale to handle large workloads **Probability:** Medium **Impact:** Medium **Mitigation:**

- Distributed architecture design
- Load testing and performance optimization
- Auto-scaling implementation

11.2 Business Risks

11.2.1 Adoption Challenges

Risk: Low user adoption due to complexity or skepticism **Probability:** Medium **Impact:** High **Mitigation:**

- Extensive user research and feedback integration
- Comprehensive training and documentation
- Success story showcases and champions program

11.2.2 ROI Shortfall

Risk: Actual cost savings may be lower than projected **Probability:** Low **Impact:** Medium **Mitigation:**

- Conservative ROI projections
- Continuous monitoring and optimization
- Flexible pricing and deployment models

11.3 Security Risks

11.3.1 Code Exposure

Risk: Proprietary algorithms may be exposed or leaked **Probability:** Low **Impact:** High **Mitigation:**

- End-to-end encryption of algorithm code
- Role-based access controls
- Regular security audits and penetration testing

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12. Budget & Resource Requirements

12.1 Infrastructure Costs

12.1.1 Development Environment

- **EKS Cluster:** $2,000/month (development)
- **Storage:** $500/month (databases, artifacts)
- **Monitoring:** $300/month (Prometheus, Grafana)
- **Total Development:** $2,800/month

12.1.2 Production Environment

- **EKS Cluster:** $8,000/month (production, staging)
- **GPU Instances:** $5,000/month (RL training)
- **Storage:** $2,000/month (production data)
- **Monitoring & Logging:** $1,000/month
- **Total Production:** $16,000/month

12.2 Personnel Costs (90-day development)

12.2.1 Engineering Team

- **Senior Backend Engineers (4):** $80K (3 months)
- **ML Engineers (2):** $45K (3 months)
- **Frontend Engineers (2):** $30K (3 months)
- **DevOps Engineer (1):** $22K (3 months)
- **Technical Writer (1):** $15K (1 month)
- **Total Personnel:** $192K

12.2.2 Additional Costs

- **Third-party Tools:** $10K (development tools, licenses)
- **Training & Conferences:** $15K (team training)
- **Contingency (15%):** $33K
- **Total Additional:** $58K

12.3 Total Investment Summary

- **Development (90 days):** $250K
- **Annual Infrastructure:** $226K

- **Total First Year:** $476K

12.4 Expected Returns

- **Annual Cost Savings:** $3.0-3.5M
- **Productivity Gains:** $800K (data scientist time)
- **Total Annual Returns:** $3.8-4.3M
- **Net ROI:** 8-9× in first year

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13. Compliance & Governance

13.1 Data Governance

- **Data Classification:** All algorithm code classified as confidential
- **Data Retention:** Optimization results retained for 2 years
- **Data Privacy:** No PII processing in optimization workflows
- **Backup & Recovery:** Daily backups with 4-hour recovery SLA

13.2 Security Compliance

- **SOC 2 Type II:** Compliance within 12 months
- **ISO 27001:** Alignment with information security standards
- **GDPR:** Data processing compliance for EU regulations
- **Regular Audits:** Quarterly security assessments

13.3 Operational Governance

- **Change Management:** Standard change control processes
- **Incident Response:** 24/7 on-call rotation for critical issues
- **Disaster Recovery:** Multi-region backup and failover
- **Business Continuity:** 99.5% uptime commitment

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14. Success Criteria & Definition of Done

14.1 Phase 1 Success Criteria

- [ ] Successfully optimize 3 different algorithm types
- [ ] Achieve minimum 5× speedup on 90% of test cases
- [ ] Deploy optimized algorithms with <1% failure rate

- [ ] Complete core infrastructure with 99% uptime

14.2 Phase 2 Success Criteria

- [ ] Optimize 10+ ML algorithms successfully
- [ ] Achieve 10× average speedup on feature selection
- [ ] Deploy production API with comprehensive documentation
- [ ] Demonstrate integration with existing ML pipelines

14.3 Phase 3 Success Criteria

- [ ] 80% adoption rate among data science teams
- [ ] Generate $1M+ in demonstrable cost savings
- [ ] Complete security audit with no critical findings
- [ ] Achieve 13× ROI through measurable benefits

14.4 Overall Success Definition

The Algorithm Optimizer will be considered successful when it:

1. Consistently improves algorithm performance by 5-45×
2. Reduces organizational cloud computing costs by >70%
3. Increases data scientist productivity by >20%
4. Maintains 99.5% system reliability
5. Achieves >13× ROI within the first year

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15. Appendices

15.1 Glossary

- **GRPO:** Group Relative Policy Optimization
- **RFE:** Recursive Feature Elimination
- **EKS:** Amazon Elastic Kubernetes Service
- **MLOps:** Machine Learning Operations
- **SLA:** Service Level Agreement
- **KPI:** Key Performance Indicator

15.2 References

- Research papers and technical documentation (see separate reference document)

- Industry benchmarks and case studies
- Technology vendor documentation

15.3 Change Log

- **v1.0 (Jan 2025):** Initial PRD creation
- Future versions will track requirement changes and scope adjustments

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Document Approval:

- [ ] Product Manager
- [ ] Engineering Director
- [ ] Data Science Director
- [ ] Chief Technology Officer
- [ ] Chief Data Scientist

Next Steps:

1. Stakeholder review and approval (Week 1)
2. Technical design document creation (Week 2)
3. Sprint planning and team formation (Week 3)
4. Development kickoff (Week 4)