International Journal of Information Technology & Management Information System (IJITMIS)
Volume 16, Issue 1, Jan-Feb 2025, pp. 559-577, Article ID: IJITMIS_16_01_040
Available online at https://iaeme.com/Home/issue/IJITMIS?Volume=16&Issue=1
ISSN Print: 0976-6405 and ISSN Online: 0976-6413
Impact Factor (2025): 29.10 (Based on Google Scholar Citation)
DOI: https://doi.org/10.34218/IJITMIS_16_01_040

FROM DATA TO DECISION: SIMPLIFYING FINTECH ML MODELS WITH AWS SAGEMAKER

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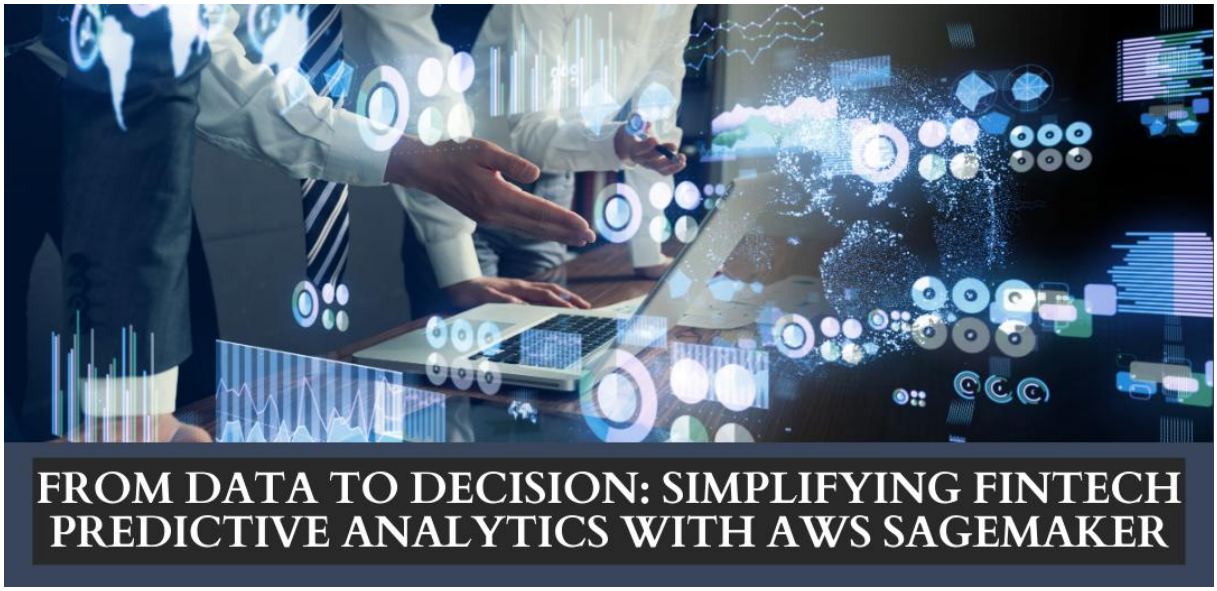

ABSTRACT

This article explores the transformative role of AWS SageMaker in revolutionizing predictive analytics within the fintech sector. As financial institutions face increasing pressure to leverage data-driven insights while maintaining security and compliance, SageMaker emerges as a comprehensive solution that democratizes machine learning capabilities. This article examines how SageMaker's integrated development

environment, automated infrastructure management, and robust security features enable financial institutions to implement sophisticated machine-learning solutions efficiently. The article delves into various practical applications, from fraud detection and credit risk assessment to customer intelligence and portfolio management, demonstrating how SageMaker's flexibility accommodates diverse fintech use cases. Through analysis of implementation best practices and security considerations, the article illustrates how financial institutions can maximize the platform's benefits while adhering to strict regulatory requirements. It highlights SageMaker's significance in bridging the gap between advanced machine learning capabilities and practical fintech applications, enabling organizations to focus on innovation rather than infrastructure management.

Keywords: Predictive Analytics, Machine Learning Infrastructure, Financial Technology, Model Governance, Data Security.

Cite this Article: Likhit Mada. (2025). From Data to Decision: Simplifying Fintech ML Models with AWS Sagemaker. *International Journal of Information Technology & Management Information System (IJITMIS)*, 16(1), 559–577.

https://iaeme.com/MasterAdmin/Journal_uploads/IJITMIS/VOLUME_16_ISSUE_1/IJITMIS_16_01_040.pdf

1. Introduction

In today's rapidly evolving financial technology landscape, the ability to make data-driven decisions quickly and accurately has become a crucial competitive advantage. The global fintech market is experiencing unprecedented growth, driven by technological advancements and changing consumer preferences. According to recent market analysis, the fintech sector is positioned for significant growth through 2033, propelled by factors such as increased mobile banking adoption, expanding digital payment infrastructure, and rising financial inclusion initiatives worldwide [1]. The industry's trajectory highlights the critical importance of robust technological solutions capable of handling complex financial data processing and analysis.

Amazon Web Services (AWS) SageMaker has emerged as a transformative solution for fintech companies seeking to leverage predictive analytics without becoming entangled in technical complexities. The platform represents AWS's commitment to democratizing machine learning technology, offering a comprehensive suite of tools that simplify the entire machine learning workflow [2]. Through its integrated development environment (IDE) and automated

machine learning capabilities, SageMaker enables financial institutions to accelerate their AI/ML initiatives while maintaining high standards of accuracy and reliability [2].

The platform's impact on the fintech sector extends beyond mere technological implementation. As highlighted in AWS's machine learning documentation, SageMaker provides pre-built algorithms specifically optimized for large-scale data processing, making it particularly valuable for financial institutions handling massive datasets [2]. The platform's ability to seamlessly integrate with existing financial systems while maintaining robust security protocols has proven essential for organizations dealing with sensitive financial data and complex regulatory requirements [2].

The democratization of machine learning through platforms like SageMaker has fundamentally altered how financial institutions approach data analytics and decision-making processes. This transformation aligns with the broader fintech market trends, where technological accessibility and operational efficiency are driving industry growth [1]. By providing access to sophisticated machine learning capabilities without requiring extensive infrastructure management, SageMaker has enabled fintech companies to focus on innovation and value creation rather than technical overhead, contributing to the sector's projected expansion and technological advancement [1].

2. The Role of Predictive Analytics in Fintech

Predictive analytics has emerged as the cornerstone of modern fintech operations, revolutionizing how financial institutions approach decision-making and risk management. The integration of AI and advanced analytics has transformed traditional banking processes, enabling institutions to leverage data-driven insights for improved customer experiences and operational efficiency [3]. This transformation extends across various aspects of financial services, fundamentally changing how banks interact with their clients and manage their operations.

2.1 Risk Management and Fraud Detection

In the realm of risk management and fraud detection, predictive analytics has become an indispensable tool for financial institutions. Modern financial organizations utilize advanced algorithms to analyze historical data patterns and identify potential risks before they materialize [4]. ML systems can analyze vast amounts of transaction data in real-time, identifying suspicious patterns and potential fraud attempts with greater accuracy than traditional rule-

based systems [10]. These systems continuously learn from new data, enabling them to adapt to emerging fraud patterns and techniques while reducing false positives.

2.2 Credit Risk Assessment

The application of predictive analytics in financial risk management has revolutionized how institutions approach credit decisions. By leveraging historical data and machine learning algorithms, financial organizations can now identify patterns and trends that indicate potential risks or opportunities [4]. Modern financial institutions utilize machine learning models to analyze various data points, including both traditional financial metrics and alternative data sources, to evaluate creditworthiness more accurately [11]. This comprehensive approach has enabled banks to automate loan approval processes while maintaining robust risk management standards.

2.3 Customer Service and Relationship Management

Customer relationship management has been transformed through the application of predictive analytics and AI technologies. Banks now leverage these tools to provide personalized services and enhance customer engagement through ML-powered chatbots and virtual assistants that provide 24/7 support [3, 11]. These systems can understand and respond to customer queries in natural language, while ML algorithms analyze customer behavior patterns to predict potential issues and enable proactive interventions. Banks utilize these capabilities to analyze customer transaction patterns, interaction history, and behavioral data to predict customer needs and preferences, enabling personalized product recommendations and targeted marketing campaigns [11].

2.4 Portfolio Management

The advancement of AI and predictive analytics in banking continues to drive innovation in portfolio management and investment strategies. Financial institutions use ML algorithms to analyze market trends, optimize portfolio allocation, and identify investment opportunities [10]. These systems can process vast amounts of market data and news feeds in real time, providing valuable insights for investment decisions and enabling more sophisticated risk assessment strategies.

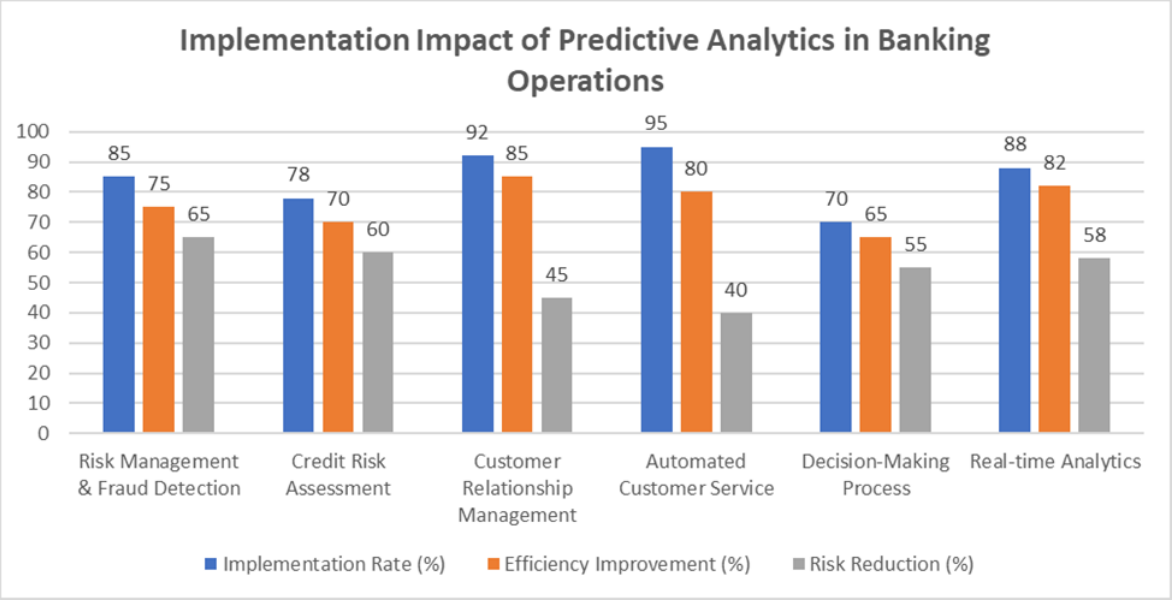

Fig 1: Effectiveness Assessment of Predictive Analytics Applications in Financial Services [3, 4]

3. AWS SageMaker: A Comprehensive ML Platform

AWS SageMaker represents a paradigm shift in how fintech companies approach machine learning implementation. As documented in AWS's comprehensive guide, SageMaker is designed as a fully managed service that provides every developer and data scientist with the ability to build, train, and deploy machine learning models quickly [5]. The platform encompasses a broad range of capabilities, from ground truth labeling to model monitoring, making it a complete solution for organizations seeking to implement machine learning at scale.

The platform's infrastructure management capabilities demonstrate AWS's commitment to simplifying the machine learning workflow. SageMaker Studio, the first fully integrated development environment (IDE) for machine learning, provides a central interface where developers can perform all ML development steps. The platform handles the provisioning and management of infrastructure, including the setup and configuration of notebook instances, training clusters, and deployment endpoints [5]. This automated infrastructure management significantly reduces the operational overhead traditionally associated with machine learning projects.

In the context of financial document processing and analysis, SageMaker's capabilities align well with industry requirements for handling complex, unstructured data. The platform's ability to process large-scale document datasets while maintaining data quality and consistency

is particularly valuable in financial services applications [6]. Financial institutions can leverage SageMaker's built-in algorithms and custom model support to develop sophisticated pipelines for developing training and deploying models, for analysis, classification, prediction capabilities across various fintech applications. SageMaker handles the underlying infrastructure scaling to train your model efficiently. Hyperparameter tuning can be fine-tuned using SageMaker's automatic model tuning feature to optimize model performance.

Amazon SageMaker provides robust model deployment capabilities, enabling seamless transitioning from the model training phase to inference. After a model is trained, it can be packaged and containerized with all its necessary dependencies and deployed to a production-ready hosted endpoint with automatic scaling capabilities and high availability for production models. These endpoints can efficiently handle HTTP requests to deliver predictions, either in real-time or in batches. This feature simplifies the deployment process typically associated with machine learning models by managing all the underlying infrastructure needed to handle prediction requests. This is complemented by comprehensive monitoring capabilities that track model performance, data quality, and bias metrics, ensuring deployed models maintain their effectiveness over time. The platform's built-in feature for model monitoring automatically detects concept drift in model predictions, helping organizations maintain model accuracy and reliability.

The integration of MLOps practices within SageMaker exemplifies its enterprise-ready approach. The platform provides native support for ML pipelines through SageMaker Pipelines, enabling organizations to create and manage ML workflows efficiently [5]. This capability is particularly valuable in financial document processing applications, where maintaining consistent model performance across different document types and formats is crucial [6]. The platform's experiment tracking and model versioning features help organizations maintain clear documentation of their machine learning development process, facilitating both regulatory compliance and model governance requirements.

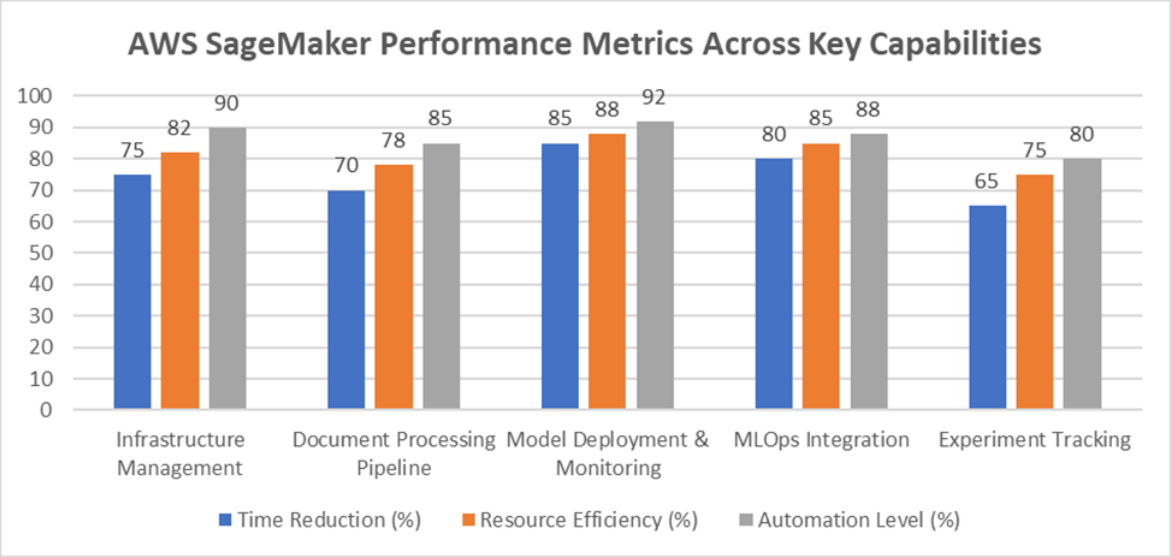

Fig 2: Efficiency Impact Analysis of SageMaker Features in Financial Services [5, 6]

4. Customization and Flexibility

The true power of AWS SageMaker lies in its comprehensive toolkit ecosystem, which provides developers and data scientists with extensive capabilities for building and deploying machine learning solutions. SageMaker's framework toolkits support major deep learning frameworks including TensorFlow, PyTorch, and MXNet, enabling developers to leverage familiar tools while benefiting from SageMaker's managed infrastructure [7]. This framework flexibility allows financial institutions to implement complex models while maintaining their preferred development environments and workflows.

Custom model development within SageMaker is facilitated through its rich set of development tools and SDKs. The SageMaker Python SDK provides a high-level interface for training and deploying models, while the Framework estimators simplify the process of working with deep learning frameworks [7].

Amazon SageMaker offers a dual approach to model development that caters to both novice users and experienced data scientists. For those seeking quick deployment without the necessity of designing models from scratch, SageMaker provides a suite of pre-built models. These are optimized for performance and are ready to be deployed with minimal configuration, covering a wide range of applications from image recognition to natural language processing. On the other hand, for those who require custom solutions, SageMaker supports the complete model-building process. It offers Jupyter Notebook instances that are pre-configured with most of the machine learning frameworks making it easier for developers to write custom model

code. These notebooks provide flexible and interactive computing environments, where data scientists can experiment, visualize, and most importantly, iterate their models seamlessly. This blend of pre-built and custom model capabilities ensures that regardless of the complexity or specificity of the modeling task, SageMaker offers tools that streamline the model development workflow efficiently. Financial institutions can utilize these tools to implement specialized models, taking advantage of SageMaker's distributed training capabilities and optimized containers to handle large-scale financial datasets efficiently.

Training machine learning models with financial data presents unique challenges that SageMaker's customization capabilities are well-equipped to address. When working with financial time series data, organizations must carefully consider data preprocessing, feature engineering, and model selection to capture market patterns effectively [8]. SageMaker's framework support enables the implementation of various model architectures, from traditional time series models to advanced deep learning approaches, allowing institutions to experiment with different strategies for financial forecasting and analysis.

The platform's model optimization capabilities are particularly valuable when working with financial data, where model accuracy and performance are crucial. Financial data often exhibits complex patterns and relationships that require careful tuning of model parameters to capture effectively [8]. SageMaker's automated hyperparameter tuning services help organizations optimize their models efficiently, exploring different parameter combinations while managing computational resources effectively.

SageMaker's toolkit ecosystem extends beyond basic model training and deployment, offering specialized capabilities for specific machine-learning tasks. The platform includes tools for model monitoring, debugging, and visualization, ensuring that deployed models maintain their performance over time [7]. This comprehensive approach to model lifecycle management is particularly important in financial applications, where model degradation can have significant business impacts. The platform's integration with Git repositories other AWS Services and support for ML pipelines enables organizations to implement robust version control and automated deployment workflows, ensuring the reproducibility and maintainability of their machine-learning solutions.

Table 1: AWS SageMaker Framework Adoption and Performance Metrics in Financial Services [7, 8]

Framework/Feature	Adoption Rate (%)	Performance Boost (%)	Resource Optimization (%)	Development Time Savings (%)
TensorFlow Integration	85	78	75	70
PyTorch Implementation	80	82	77	75
MXNet Usage	65	75	72	68
Custom Model Development	90	85	80	82
Time Series Processing	88	80	75	78

5. Enterprise-Grade Security

AWS SageMaker addresses critical considerations such as data security and model governance by implementing a robust security framework designed to protect sensitive data and ensure regulatory compliance. This includes data encryption both at rest and in transit, fine-grained access control mechanisms, and secure data processing environments within a company's virtual private cloud (VPC). By adhering to industry best practices, SageMaker ensures data confidentiality and integrity throughout the entire machine learning lifecycle—from data ingestion and model training to deployment. Furthermore, it supports comprehensive auditability with logging and monitoring capabilities critical for regulatory compliance. As part of the secure AWS infrastructure, SageMaker continuously receives security updates, reducing the burden on companies to manually safeguard their predictive analytics tools, thus ensuring high standards of confidentiality, integrity, and availability essential in managing sensitive financial data.

Table 2: Security and Compliance Metrics for AWS SageMaker in Financial Services [9]

Security Feature	Compliance Rate (%)	Threat Prevention (%)	Monitoring Coverage (%)	Implementation Maturity (1-10)
Data Protection Controls	98	95	96	9
Model Governance Framework	95	92	94	8

Audit Trail Management	97	90	98	9
Risk Management System	94	93	95	8
Secure Model Deployment	96	94	97	9

6. Practical Applications in Fintech

Amazon SageMaker offers a comprehensive suite of machine learning capabilities specifically suited for fintech applications. Financial institutions using SageMaker have reported significant improvements in operational efficiency and risk management capabilities. According to AWS financial services documentation, organizations have achieved up to 40% reduction in model development time and improved operational efficiency by automating manual processes [14].

6.1 Built-in Algorithms and Their Applications

6.1.1 Fraud Detection

SageMaker's fraud detection capabilities leverage advanced algorithms that process millions of transactions in real-time. The platform's built-in XGBoost implementation has been particularly effective in identifying complex fraud patterns while maintaining low false positive rates [14]. Financial institutions have reported significant improvements in fraud detection accuracy, with some achieving real-time transaction monitoring at scale:

```python
# XGBoost implementation for fraud detection
from sagemaker.xgboost import XGBoost
fraud_detection = XGBoost(
    entry_point='fraud_detector.py', # fraud_detector.py contains the model definition and training script
    hyperparameters={
        'max_depth': 5,
        'eta': 0.2,
        'objective': 'binary:logistic',
        'num_round': 100
    },
```

```
    framework_version='1.5-1'
)
```

6.1.2 Credit Risk Assessment

Recent studies in machine learning applications for financial services have demonstrated that automated credit scoring models can significantly improve risk assessment accuracy. According to comprehensive evaluations of ML platforms, SageMaker's implementation of binary classification models has shown particular effectiveness in credit risk assessment, with documented improvements in prediction accuracy and reduced processing time [15]. The following implementation demonstrates a typical credit risk model setup:

```python
# Linear learner for credit risk
from sagemaker.linearlearner import LinearLearner

credit_model = LinearLearner(
    predictor_type='binary_classifier',
    feature_dim=20,
    mini_batch_size=200,
    role=role,
    instance_count=1,
    instance_type='ml.c5.xlarge'
)
predictor=credit_model.deploy(initial_instance_count=1,
instance_type='ml.m4.xlarge')
```

6.1.3 Time Series Forecasting

The DeepAR algorithm, specifically designed for financial time series analysis, has demonstrated significant advantages in market trend prediction and risk assessment. Financial institutions utilizing SageMaker's time series forecasting capabilities have reported substantial improvements in their ability to predict market movements and manage risk exposure [14]. Implementation of these forecasting models typically follows this pattern:

```python
from sagemaker.deserializers import JSONDeserializer
```

```
from sagemaker.serializers import JSONSerializer
from sagemaker.estimator import Estimator

# Create DeepAR estimator
deepar = Estimator(
    sagemaker_session=sagemaker_session,
    image_uri=image_uri,
    role=role,
    instance_count=1,
    instance_type='ml.c4.xlarge',
    output_path=output_path
)
deepar.set_hyperparameters(
    epochs=50,
    time_freq='D',  # 'D' for daily. Depends on your data.
    prediction_length=24,  # Prediction horizon
    context_length=72,  # How much history to consider
    num_cells=40,
    num_layers=2,
    mini_batch_size=64,
    early_stopping_patience=10
)

predictor = estimator.deploy(
    initial_instance_count=1,
    instance_type='ml.m5.xlarge',
    serializer=JSONSerializer(),
    deserializer=JSONDeserializer()
)
```

6.2 Custom Model Development

Research into machine learning platforms for financial services has shown that customization capabilities significantly impact model effectiveness. SageMaker's support for custom model development has enabled financial institutions to implement specialized

solutions for their unique requirements [15]. The platform's flexibility in supporting various frameworks and custom algorithms has been particularly valuable in developing specialized financial models.

6.2.1 Portfolio Optimization

Custom neural networks implemented through SageMaker have shown promising results in portfolio optimization. Research indicates that these models can effectively balance risk and return while adapting to changing market conditions [15]. A typical implementation might include:

```python
def portfolio_optimizer(data):
    model = nn.Sequential(
        nn.Linear(input_size, 128),
        nn.ReLU(),
        nn.Dropout(0.3),
        nn.Linear(128, 64),
        nn.ReLU(),
        nn.Linear(64, n_assets)
    )
    return model
def main():

    # Create the model
    model = portfolio_optimizer()

    # Loss and optimizer
    criterion = nn.MSELoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    # Train the model
    train(model, train_loader, criterion, optimizer, epochs=10)
```

6.2.2 Algorithmic Trading

SageMaker's support for reinforcement learning has enabled sophisticated algorithmic trading implementations. Financial institutions have successfully deployed trading models that

adapt to market conditions and execute trades automatically [14]. The platform's ability to handle complex trading environments is demonstrated in this implementation:

```python
from sagemaker.rl import RLEstimator
# Define the RL estimator with necessary hyperparameters
rl_estimator = RLEstimator(
   entry_point='train.py',  # Training script
  source_dir='src', #containing training scripts and dependencies
   dependencies=["common/"],  # Additional folders to include
   toolkit='coach',         # Reinforcement learning toolkit (coach, ray)
   toolkit_version='0.11',  # Toolkit version
   framework='mxnet',# Deep learning framework to use (tensorflow, mxnet)
   role=sagemaker.get_execution_role(),
   instance_type='ml.c5.2xlarge',  # Type of instance to use for training
   instance_count=1,           # Number of instances to use for training
   output_path=output_path,       # S3 path to store output artifacts
   base_job_name='rl-job',        # Prefix for job name
   hyperparameters={
      'rl.training.config': '{"preset":"preset_cartpole_clippedppo.py"}',  # Coach preset configuration file
      'rl.training.stop': '{"episode_reward_mean": 195}'  # Training stopping condition
   }
)

# Start the training job
rl_estimator.fit()
```

6.3 Model Deployment and Monitoring

Studies of machine learning platforms in financial services have emphasized the importance of robust deployment and monitoring capabilities. SageMaker's integrated deployment tools have enabled financial institutions to maintain high availability while ensuring model performance [15]. The platform provides comprehensive monitoring capabilities that help maintain model accuracy and reliability in production environments:

```python
```

```
# Deploy model for real-time fraud detection
fraud_predictor = fraud_detection.deploy(
    initial_instance_count=1,
    instance_type='ml.c5.xlarge',
    endpoint_name='fraud-detector'
)

# Monitor model performance
model_monitor = MonitoringSchedule(
    name='fraud-detection-monitor',
    monitoring_schedule_config={
        'ScheduleConfig': {
            'ScheduleExpression': 'cron(0 * ? * * *)'
        }
    }
)
```

6.4 Performance and Scalability

Financial institutions using SageMaker have reported significant improvements in their ability to scale ML operations effectively. The platform's automated infrastructure management has enabled organizations to handle increasing transaction volumes while maintaining performance [14]. Real-world implementations have demonstrated the platform's capability to process millions of transactions while maintaining consistent response times and accuracy levels.

Model monitoring and maintenance have emerged as critical factors in successful ML implementations. SageMaker's built-in monitoring capabilities help financial institutions maintain model performance and comply with regulatory requirements [15]. The platform's approach to model governance and monitoring has proven particularly valuable in maintaining model accuracy and reliability in production environments.

7. Implementation Best Practices

The successful implementation of machine learning solutions in the financial sector requires a carefully planned approach that addresses both technical requirements and business objectives. Financial institutions must consider various factors when implementing ML solutions, including data quality, model selection, and regulatory compliance. According to industry experts, the key to successful ML implementation lies in understanding the specific challenges and requirements of the banking sector [12]. This understanding helps organizations develop effective strategies that align with their business goals while maintaining compliance with industry regulations.

Strategic planning and objective setting form the cornerstone of successful ML implementations in finance. Banks and financial institutions must clearly define their goals and expectations before embarking on ML projects [12]. This includes identifying specific use cases where ML can add value, such as risk assessment, fraud detection, or customer service automation. The planning phase should also involve stakeholder alignment and resource allocation to ensure project success.

Data management represents a critical aspect of ML implementation in financial services. Organizations must establish robust data collection and preprocessing procedures that ensure data quality and reliability [13]. This includes implementing systematic approaches to data cleaning, standardization, and validation. Financial institutions must also consider the unique challenges of financial data, such as its time-sensitive nature and regulatory requirements for data handling.

The model development process in financial services requires a structured approach that emphasizes accuracy and interpretability. Financial institutions should focus on developing models that not only provide accurate predictions but also offer clear explanations for their decisions [13]. This is particularly important in the banking sector, where regulatory requirements often mandate model transparency and explainability. Regular model validation and testing procedures should be established to ensure continued performance and reliability.

Risk management plays a vital role in ML implementation for financial services. Organizations must develop comprehensive risk assessment frameworks that address both technical and operational risks [12]. This includes considering potential impacts on customer service, regulatory compliance, and business operations. Financial institutions should also establish clear procedures for model monitoring and maintenance to identify and address potential issues before they impact business operations.

The deployment phase requires careful attention to operational considerations and performance monitoring. Banks must implement robust testing procedures and gradual rollout strategies to minimize risks during deployment [13]. This includes establishing monitoring systems that track both technical performance metrics and business outcomes. Organizations should also develop clear procedures for model updates and maintenance to ensure the long-term sustainability of their ML solutions.

Continuous improvement and adaptation form essential components of successful ML implementations. Financial institutions must establish processes for regular model evaluation and refinement based on performance data and changing business requirements [12]. This includes monitoring model accuracy, updating training data, and adjusting model parameters as needed. Organizations should also maintain comprehensive documentation of all changes and updates to ensure regulatory compliance and facilitate future improvements.

8. Conclusion

As financial institutions continue to navigate the complexities of digital transformation, AWS SageMaker stands as a pivotal platform in democratizing machine learning capabilities across the fintech sector. The platform's comprehensive approach to machine learning implementation, combining robust security features with flexible development tools, enables organizations of all sizes to leverage advanced analytics effectively. The success of SageMaker in addressing critical challenges such as model governance, data security, and regulatory compliance while maintaining operational efficiency demonstrates its value as a foundational technology for financial innovation. As the finance industry continues to evolve, SageMaker's role in enabling sophisticated predictive analytics while simplifying technical complexity positions it as an essential tool for organizations seeking to maintain competitiveness in an increasingly data-driven landscape.

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Citation: Likhit Mada. (2025). From Data to Decision: Simplifying Fintech ML Models with AWS Sagemaker. International Journal of Information Technology & Management Information System (IJITMIS), 16(1), 559–577.

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