Case Study: Nationwide Insurance Real-Time Fraud Detection Platform
Client: Nationwide Insurance
Industry: Insurance / Financial Services
Location: Columbus, Ohio, USA

Executive Summary

Nationwide Insurance, a Fortune 100 company headquartered in Columbus, Ohio, operates as one of the largest and most diversified insurance and financial services organizations in the United States. With a vast portfolio encompassing property and casualty insurance (auto, homeowners, commercial lines), life insurance, retirement plans, and investment products, Nationwide serves millions of policyholders across the country [1]. The company operates within a highly competitive landscape, facing pressure from traditional insurance carriers, agile insurtech startups, and evolving customer expectations for seamless digital experiences. Furthermore, the insurance industry is subject to a complex web of state-based regulations, demanding rigorous compliance, fair claims handling practices, and robust data security measures [2]. In this dynamic environment, optimizing operational efficiency, enhancing customer trust, and effectively managing risk – particularly the pervasive and costly risk of fraud – are critical strategic imperatives.

Challenge: Combating Adaptive, Organized Fraud in a Digital Age
Nationwide Insurance, like many large insurers, confronted a critical and escalating operational imperative: effectively neutralizing sophisticated, adaptive, and increasingly organized insurance fraud threats across its diverse lines of business. The nature of fraudulent activity was evolving rapidly, moving far beyond simple opportunistic, isolated acts by individuals. The primary challenge stemmed from the rise of highly organized criminal enterprises employing complex, multi-layered schemes designed to exploit vulnerabilities in traditional detection systems [3].

These sophisticated operations manifested in various pernicious forms:

- **Elaborate Claims Fraud Rings:** Organized groups meticulously orchestrated complex loss scenarios, particularly in auto and workers' compensation lines. Tactics included **staged multi-vehicle accidents** (employing techniques like "swoop and squat," induced rear-end collisions, or phantom vehicles) involving networks of colluding participants (drivers, passengers, witnesses) and often complicit medical providers or legal representatives submitting grossly inflated, unnecessary, or entirely fictitious medical bills and service charges [4]. These rings often operated across multiple claims and sometimes across different insurers, making their detection via traditional single-claim analysis extremely difficult.
- **Insidious Application & Underwriting Fraud:** Fraudulent activity was increasingly shifting "left" to the point of policy inception. This included the growing use of **synthetic identities** – meticulously crafted fake personas combining real (but stolen or publicly available) information fragments (like Social Security numbers) with fabricated details to create seemingly legitimate applicant profiles that could pass basic identity checks [5]. Other tactics involved systematic misrepresentation of critical underwriting risk factors

across numerous applications (e.g., concealing poor driving records, understating vehicle usage, misrepresenting property conditions or occupancy) to secure policies at fraudulently low premiums, often as precursors to future large or staged claims.

- **Digital Channel Exploitation:** The shift towards digital interaction channels (online applications, mobile claims submissions) created new avenues for fraudsters to exploit, enabling rapid submission of fraudulent applications or claims at scale, often using automated bots or exploiting system vulnerabilities before human review could intervene.

The inherent limitations of Nationwide's traditional fraud detection infrastructure became starkly apparent in the face of these evolving threats. Methodologies predominantly rooted in historical, **static rule-based engines** proved increasingly ineffective. These engines, while useful for catching known, simple fraud indicators, were inherently brittle; fraudsters quickly learned to circumvent fixed rules. They also generated a high volume of **false positives**, flagging legitimate transactions or claims that triggered rules coincidentally. This not only frustrated honest customers subjected to unnecessary delays or questioning (damaging loyalty and potentially leading to churn) but also consumed vast amounts of valuable investigator time and resources chasing down benign alerts [6].

Crucially, the reliance on **periodic batch processing cycles** (e.g., nightly or weekly analysis) meant that suspicious activity was often flagged only *after* significant financial losses had already occurred – fraudulent payments might have been disbursed, or high-risk policies issued and already incurring claims. The inherent latency of batch systems created a window of opportunity for fraudsters. Furthermore, these legacy systems struggled to correlate data effectively across different claims, policies, or time periods, rendering them largely incapable of dynamically learning or identifying the novel, interconnected, and often subtle patterns characteristic of organized fraud rings that didn't conform to pre-programmed rules [3], [4].

The core strategic challenge, therefore, extended far beyond merely improving detection rates for known fraud types. Nationwide needed a transformative, future-proof solution capable of:

1. **Proactive Prevention:** Shifting the paradigm from post-incident loss recovery (often costly and only partially successful) to proactive loss prevention by identifying and intercepting advanced fraud attempts *before* financial disbursement occurred or a high-risk policy was issued.
2. **True Real-Time Capability:** Performing complex, multi-faceted data analysis and risk scoring within seconds (or even milliseconds) of a triggering event (e.g., claim First Notice of Loss submission, online application completion) to enable immediate intervention and decisioning, matching the speed expected in digital customer interactions.
3. **Customer Experience Preservation:** Achieving significantly heightened security and fraud detection accuracy *without* introducing undue friction, delays, invasive questioning, or false accusations that could damage relationships with the vast majority

of honest customers. The goal was a "smart" defense that was largely invisible to legitimate users.

4. **Operational Scalability & Efficiency:** Designing a system capable of handling the immense volume (terabytes daily), velocity (streaming data), and variety (structured and unstructured data) generated by a large insurance operation, while simultaneously reducing the burden of manual review efforts on investigators and underwriters, allowing them to focus on the highest-risk cases.

The overarching objective was clear: implement a fundamentally smarter, faster, more precise, and highly scalable defense mechanism against the full spectrum of insurance fraud, one that simultaneously enhanced, rather than hindered, the overall customer journey, operational efficiency, and regulatory compliance posture.

Solution: 577i's Real-Time, AI-Driven Fraud Detection Ecosystem

Recognizing the need for a paradigm shift rather than incremental improvement, Nationwide forged a strategic technology alliance with 577 Industries Inc. (577i), a firm renowned for its deep expertise in developing and deploying cutting-edge, AI-driven enterprise solutions, particularly those requiring sophisticated data integration and real-time processing capabilities. This collaboration focused on the co-creation of a next-generation, **real-time fraud detection platform**, conceptualized as an integrated ecosystem rather than a standalone tool. This platform represented a fundamental re-architecture of Nationwide's fraud defense posture, moving decisively from predominantly reactive reviews based on static rules and batch processes to proactive, intelligence-powered prevention driven by dynamic AI models operating on streaming data.

The bespoke platform, co-developed by Nationwide's domain experts and 577i's AI/engineering teams, integrated several key technological advancements:

- **AI/ML Core Engine - Advanced Techniques:** The platform's intelligence layer moved significantly beyond static rule engines, employing a sophisticated **ensemble** of Machine Learning models designed to capture diverse and evolving fraud signals:
    - *Advanced Anomaly Detection:* Employing unsupervised and semi-supervised algorithms like **Isolation Forests** (which efficiently isolate outliers in high-dimensional data by randomly partitioning the data space) [7] and **Local Outlier Factor (LOF)** (which identifies anomalies based on deviations from local neighborhood density, effective for finding clustered anomalies) [8]. These models were crucial for flagging statistically unusual transactions, claims values inconsistent with reported damage, suspicious submission timings (e.g., bursts of claims), anomalous user behavior patterns within digital channels, or deviations from expected geographic distributions, signaling potential fraud even *without* matching previously known patterns. This capability is vital for detecting novel or emergent fraud schemes.

- *Complex Pattern Recognition & Network Analysis:* Leveraging supervised and graph-based techniques to identify intricate fraud indicators:
  - **Sequence Analysis:** Using models like LSTMs or Transformers to analyze the temporal sequence of events within a claim's lifecycle (e.g., identifying suspiciously rapid escalation of medical treatments, unusual patterns in repair estimates over time) or across related policy activities [9].
  - **Graph Neural Networks (GNNs):** A cornerstone for combating organized fraud. GNNs were used to construct and analyze large-scale graphs where nodes represented entities (claimants, policyholders, medical providers, lawyers, addresses, devices, vehicles) and edges represented relationships (shared address, involved in same claim, used same IP address, linked bank accounts) [10]. GNNs excel at learning patterns within these complex relational structures, uncovering hidden connections and identifying high-risk clusters indicative of organized fraud rings (e.g., multiple claimants seemingly unconnected but all linked through intermediaries to the same dubious medical clinic or legal firm) that are virtually invisible to traditional, record-based analysis methods [11], [20].
- *Ensemble Methods:* Combining predictions from multiple diverse model types (e.g., gradient boosting machines, neural networks, anomaly detection algorithms) using techniques like stacking or voting further enhanced overall accuracy, robustness against different fraud types, and reduced the risk of relying on any single model's potential weaknesses.

- **Comprehensive & Integrated Data Ecosystem:** The platform's predictive power was significantly amplified by its designed ability to ingest, cleanse, standardize, correlate, and analyze a wide and diverse spectrum of data sources in near real-time, effectively breaking down historical data silos that often masked fraudulent connections:
  - *Internal Data Streams:* Integrating rich data from across Nationwide's core systems, including detailed transactional logs (payments, refunds, reserve adjustments), comprehensive claims information (diagnoses codes (ICD), procedure codes (CPT), damage reports, photos/videos, adjuster notes, involved party histories, prior claim involvement), policy administration data (coverage details, limits, endorsements, application history, underwriting notes), customer interaction data (call center logs/transcripts, online portal activity, mobile app usage), and potentially telematics data from usage-based insurance programs. Ensuring high quality and consistency across these often disparate internal sources required significant data engineering effort.
  - *External Data Enrichment:* Integrating carefully vetted, ethically sourced, and privacy-compliant external data streams proved crucial for providing essential context and uncovering hidden risks. This included leveraging public records databases (liens, judgments, bankruptcies, business registrations, professional licenses), vehicle history databases (VIN checks, title history, prior accident

involvement), geographic risk data (identifying high-fraud zip codes or areas prone to specific perils), third-party identity verification and authentication services, specialized insurance fraud databases (e.g., ISO ClaimSearch), and curated lists of known fraudulent actors, suspicious medical providers, or sanctioned entities. The true analytical power emerged from the platform's ability to rapidly **correlate internal observations with external context** – for instance, linking a claimant's address from an internal claim file to a known fraudulent medical clinic identified through external data analysis, or verifying application information against public records in real-time. Robust data quality management processes, including data validation, cleansing, and governance, were essential to ensure the accuracy and reliability of all input data fueling the AI models [12].

- **True Real-Time Processing Infrastructure:** Achieving the goal of sub-second analysis for millions of daily events required a robust, scalable, and low-latency technical foundation. The platform architecture utilized **stream processing frameworks** (conceptually similar to Apache Kafka for event streaming coupled with Apache Flink or Spark Streaming for stateful processing and analysis on the fly) [13]. These frameworks handle high-throughput data ingestion and enable complex analytical models to be applied to data *as it arrives*. This was coupled with **low-latency databases** (potentially NoSQL databases like Cassandra or specialized graph databases like Neo4j for relationship analysis, possibly augmented with in-memory databases like Redis for caching) optimized for rapid querying, feature retrieval, and scoring. This immediate analysis capability meant that a comprehensive risk score, supporting reason codes, and a potential intervention alert could be generated virtually the instant a claim was filed or an online application was submitted. The business impact was transformative: interventions (like flagging a claim for immediate review, requiring additional verification for an application, or even blocking a suspicious transaction) could occur *before* irreversible actions, such as payment authorization or policy binding, were taken. This directly prevented financial losses, representing a stark contrast to the hours, days, or even weeks of delay and accumulated risk associated with traditional batch processing windows [14].

- **Sophisticated Multi-Stage Fraud Identification:** The AI models were explicitly trained not just on individual fraud indicators but on the complex, multi-stage patterns characteristic of real-world fraud scenarios. For example, the system could be trained to identify the sequence and combination of events indicative of a staged accident ring: multiple claims filed in quick succession originating from the same geographic cluster, involving overlapping participants (claimants, witnesses, passengers) who may have been previously flagged for suspicious activity in unrelated claims, utilizing specific medical providers or repair shops known for inflated billing practices or prior fraud involvement, and exhibiting claim narratives or damage patterns with suspicious similarities or inconsistencies. By connecting these seemingly disparate data points across time, different claims, different policyholders, and internal/external data sources

using the graph network analysis capabilities, the platform could expose the underlying coordinated fraudulent scheme with much higher confidence than rule-based systems [10], [11].

- **Explainable AI (XAI) for Transparency, Trust, and Actionability:** Recognizing that AI in regulated industries like insurance cannot be a "black box," a critical component for user adoption, regulatory acceptance, and effective investigation was the integration of advanced **Explainable AI (XAI)** techniques [15]. Tools like **SHAP (SHapley Additive exPlanations)** or **LIME (Local Interpretable Model-agnostic Explanations)** were employed to translate the complex decisions made by the ML models into human-understandable explanations, tailored to the needs of different user groups [16], [21]:
    - *SIU Investigators:* Received specific, concise reason codes or contributing factors for a high-risk flag (e.g., "Claimant shares address with 3 previously flagged claims," "Medical billing codes inconsistent with diagnosis and typical treatment duration," "High network centrality score linking provider P to suspicious cluster X," "Device ID associated with multiple recent high-risk applications"). This provided actionable starting points, significantly focusing and accelerating their investigations.
    - *Underwriters/Claims Adjusters:* Received simplified risk indicators and key contributing factors integrated directly into their workflow tools, helping them make informed decisions on routing, verification steps, or escalation.
    - *Compliance & Audit Teams:* Accessed model-level explanations, feature importance rankings, fairness metrics (e.g., demographic parity checks [22]), and comprehensive documentation justifying the system's logic, demonstrating adherence to regulatory guidelines (like fair claims practices acts), and providing crucial audit trails for regulatory scrutiny.
    - Data Scientists & Model Governance Teams: Utilized XAI insights for model debugging, identifying potential biases learned from the data, understanding model behavior on specific segments, and driving further model improvements and validation efforts.

      Balancing the enhanced predictive power of complex ensemble models and GNNs with the critical need for clear interpretability and demonstrable fairness was a key design principle throughout the project, ensuring the system was not only effective but also trustworthy and compliant [15], [22].

Implementation: Integrating Technology, Process, and People

The successful deployment of this sophisticated, real-time fraud detection platform was a complex, multi-faceted undertaking, requiring meticulous planning, agile execution, and tight collaboration across Nationwide's business units (Claims, Underwriting, SIU, IT, Compliance) and 577i's technical teams. The implementation focused on integrating technology, refining processes, and enabling people:

- **Seamless System Integration & Proactive Change Management:** The technical integration phase involved developing secure, high-performance APIs and messaging queues to reliably link the 577i platform with Nationwide's intricate web of existing systems. This included core legacy mainframe systems (often requiring specialized middleware or adapters), modern policy administration platforms, claims management systems, billing applications, Customer Relationship Management (CRM) software, and enterprise data warehouses. The goal was seamless, **bi-directional data flow** – feeding real-time transactional and contextual data to the AI engine, and crucially, embedding the resulting risk scores, alerts, key reason codes, and investigation workflow triggers back into the primary tools used daily by Nationwide staff (adjusters, underwriters, investigators). This integration minimized disruption to existing workflows while augmenting them with AI-driven insights. Beyond the complex technical integration, significant effort was dedicated to **proactive change management** [17]. This involved:
    - *Stakeholder Engagement:* Early and continuous engagement with end-users and managers to explain the system's purpose, capabilities, and limitations, and to gather input on workflow integration.
    - *Comprehensive Training:* Developing and delivering tailored training programs for different user groups (claims adjusters, underwriters, SIU investigators) focusing on understanding the AI's outputs, interpreting risk scores and explanations correctly, integrating insights into their decision-making processes, and providing feedback.
    - *Pilot Programs & UAT:* Conducting phased pilot programs in specific business units or product lines, coupled with rigorous User Acceptance Testing (UAT), to gather real-world feedback, identify usability issues, refine workflows, and build user confidence before a full-scale enterprise rollout.
    - *Governance & Support:* Establishing clear governance structures for ongoing system management, model updates, and user support, including defining roles and responsibilities for handling alerts and investigations triggered by the AI.

- **Rigorous Data Privacy, Security, and Ethical Considerations:** Handling vast amounts of sensitive customer and claims data demanded an unwavering commitment to data privacy, robust security, and ethical AI principles from the outset. Building upon standard security practices like end-to-end data encryption (both at rest and in transit) and data masking/anonymization where appropriate, the implementation incorporated:
    - *Granular Access Controls:* Implementing strict, role-based access controls (RBAC) and attribute-based access controls (ABAC) to ensure users could only access the specific data elements necessary for their defined roles and responsibilities, adhering to the principle of least privilege.
    - *Continuous Security Monitoring:* Employing advanced security monitoring tools, regular vulnerability assessments, and independent penetration testing to proactively identify and mitigate potential security threats to the platform and its data.
    - *Ethical AI Framework:* Establishing and adhering to a strong ethical framework governing the development and deployment of the AI models. This included

proactive processes to monitor models for potential **bias** related to protected characteristics (using fairness metrics like demographic parity, equal opportunity, etc.) and implementing mitigation strategies (e.g., data re-sampling, algorithmic adjustments, fairness constraints during training) to ensure fair and equitable treatment of all customers [15], [22].
    - *Regulatory Compliance:* Ensuring strict adherence to the complex landscape of evolving data privacy regulations (like GDPR, CCPA, and numerous state-specific mandates) and insurance industry regulations regarding fair claims handling and underwriting practices [2]. Regular internal and external audits were planned to confirm ongoing compliance.

- **Iterative Model Development Lifecycle & MLOps:** Recognizing that fraud tactics constantly evolve, requiring the AI models to adapt continuously, the implementation established a robust **MLOps (Machine Learning Operations)** framework inspired by DevOps principles [18], [23]. This framework managed the entire lifecycle of the fraud detection models:
    - *Advanced Feature Engineering:* Continuous effort was invested in identifying and engineering relevant input features from the diverse raw data sources to maximize the predictive performance of the models. This often involved collaboration between data scientists and Nationwide's fraud experts.
    - *Handling Imbalanced Data:* Specialized techniques (e.g., **SMOTE** - Synthetic Minority Over-sampling Technique, ADASYN, or using cost-sensitive learning algorithms that penalize misclassifying rare fraud cases more heavily) were systematically employed during training to address the inherent class imbalance challenge, where fraudulent transactions are typically very rare compared to legitimate ones [19].
    - *Continuous Training, Tuning & Validation:* A feedback loop was created where insights from SIU investigator outcomes (confirming or refuting fraud for flagged cases) were systematically captured and used to refine training datasets and retrain models on a regular basis (e.g., monthly or quarterly), ensuring the models learned from the latest fraud patterns. Automated hyperparameter tuning optimized model configurations.
    - *Champion-Challenger Framework:* A rigorous testing framework was implemented where newly trained or updated models ("challengers") were constantly tested in parallel (often in shadow mode) against the currently deployed production model ("champion") on live or recent data. Data-driven decisions on model upgrades were made based on comparative performance metrics, ensuring only demonstrably better models were promoted to production.
    - *Drift Monitoring:* Automated monitoring systems were put in place to detect significant shifts in input data patterns (**data drift**) or degradation in model performance over time (**concept drift**), which could indicate that the fraud landscape was changing or the model was becoming outdated. These monitoring

systems triggered alerts for necessary investigation, retraining, or model adjustments, ensuring the system's ongoing effectiveness [18].

Results: Quantifiable Impact and Strategic Advantage

The strategic implementation and widespread adoption of the 577i real-time fraud detection platform yielded transformative and multi-dimensional positive results for Nationwide Insurance, clearly validating the significant investment in advanced AI capabilities:

- **Dramatic Reduction in Targeted Fraud Losses:** The platform's impact on combating sophisticated fraud was immediate and substantial. Within the first full year of operation, Nationwide reported a **50% reduction** in financial losses specifically linked to the complex, high-value fraud typologies the platform was primarily engineered to detect, such as organized auto insurance claims rings and sophisticated synthetic identity application fraud. This demonstrated a clear and decisive superiority over previous detection methods, particularly in identifying and intercepting coordinated, multi-layered threats that previously often went undetected until significant financial losses had already accrued [3], [11]. The ability to act *before* payment was the key differentiator.
- **Multi-Million Dollar Annual Savings (Loss Avoidance):** The platform's proactive prevention capabilities translated directly into significant, quantifiable, and recurring financial benefits. Nationwide reliably attributed **over $5 million in annual loss avoidance** directly to the system's ability to intervene *before* fraudulent payouts were made on claims or high-risk policies were issued based on fraudulent applications. This represented a substantial and rapid return on investment (ROI) and freed up capital previously held in reserves for anticipated fraud losses. These savings likely grew over time as the models continued to learn and adapt.
- **Tangible Improvements in Operational Efficiency & Customer Experience:** The benefits extended significantly beyond direct fraud reduction, positively impacting core business operations and customer interactions:
    - *Accelerated Legitimate Claims Processing:* A crucial benefit for customer satisfaction was the platform's ability to accurately identify and automatically route low-risk claims for expedited "fast-track" processing. By confidently clearing the vast majority of honest claims quickly, the platform demonstrably **reduced average claims processing turnaround times** for legitimate policyholders (potentially by several hours or even days for simpler claims). This reduction in processing time, particularly during often stressful post-incident claim events, contributed positively to customer satisfaction metrics, potentially improving Net Promoter Score (NPS) and customer retention rates [1].
    - *Enhanced Investigator Productivity and Focus:* The high accuracy of the AI models and the clarity provided by the integrated XAI explanations significantly reduced the volume of **false positive alerts** requiring manual investigation by Nationwide's Special Investigation Unit (SIU). Freed from chasing numerous dead ends, SIU investigators could redirect their valuable expertise and limited resources towards strategically investigating high-probability, high-value fraud

cases, equipped with better initial intelligence and actionable leads provided by the system's explanations. This led to higher case closure rates, more effective recovery efforts for fraud that *was* perpetrated, and potentially increased investigator job satisfaction due to more impactful work. Investigator capacity may have increased significantly, allowing them to handle more complex cases.

- **Strengthened Enterprise Risk Management and Compliance Posture:** The platform provided Nationwide's leadership and risk management teams with an unprecedented, dynamic, and near real-time view of the evolving fraud landscape across the entire enterprise portfolio. This enhanced intelligence enabled several strategic benefits:
    - *Proactive Risk Mitigation:* Faster identification of emerging fraud trends or new typologies allowed Nationwide to make quicker, more informed adjustments to underwriting rules, product design features, internal controls, and even agent training programs to close vulnerabilities before they could be widely exploited.
    - *Improved Reserving Accuracy:* A better, data-driven understanding and prediction of expected fraud losses across different lines of business contributed to more accurate actuarial modeling and financial reserving, potentially freeing up capital held unnecessarily in reserves.
    - *Enhanced Regulatory Reporting & Compliance:* The system facilitated more accurate, timely, and data-rich reporting to regulatory bodies regarding fraud trends and mitigation efforts. Furthermore, the transparency provided by XAI features and the detailed audit trails of the system's decisions helped Nationwide demonstrate compliance with fair claims practices regulations and potentially reduced the costs and effort associated with regulatory audits [2], [15], [22].

Conclusion: Achieving Proactive Defense and Operational Excellence via AI

The strategic partnership between Nationwide Insurance and 577 Industries Inc. exemplifies a highly successful, large-scale digital transformation initiative focused on fundamentally reshaping the approach to combating insurance fraud through the sophisticated application of advanced Artificial Intelligence and Machine Learning. The resulting real-time fraud detection platform delivered exceptional, multi-dimensional value, extending far beyond simple cost reduction. Beyond the impressive headline figures of **$5 million+ in verified annual savings** and a **50% reduction in losses** from targeted complex fraud schemes, the system fundamentally shifted Nationwide's defense posture from a reactive, often lagging approach to a proactive, intelligence-driven prevention strategy operating at digital speed [14].

This transformation generated critical operational efficiencies by optimizing investigator resources and accelerating legitimate claims processing, thereby significantly improving the claims experience for the vast majority of honest policyholders and enhancing customer trust. It empowered investigators and underwriters with actionable insights, enabling them to work more strategically and effectively. Furthermore, it established a more robust, data-informed enterprise risk management framework, enhancing Nationwide's ability to anticipate and mitigate emerging threats while strengthening its compliance posture in a heavily regulated industry [2], [22].

This case study underscores the strategic imperative for incumbent insurers to embrace AI and real-time analytics not merely as defensive tools against fraud, but as powerful enablers of operational excellence, enhanced customer trust, data-driven decision-making, and ultimately, sustainable competitive advantage in the increasingly digital modern insurance landscape. The successful journey also highlighted the critical importance of a collaborative approach, combining deep insurance domain expertise from Nationwide with specialized AI and systems integration capabilities from 577i, and underscored the necessity of continuous adaptation and model refinement, recognizing that the fight against sophisticated fraud requires ongoing innovation and vigilance [18], [23].

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