Game-Generated Data: An Untapped Resource for Advanced AI Training

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Abstract

Game-generated data represents an untapped resource for AI training, offering unique characteristics that address critical limitations in current approaches. With high-quality text data projected to be exhausted by 2026-2032, gaming platforms generate terabytes of rich behavioural data daily that remains largely underutilised. This paper examines how gaming data's natural properties—causal relationship preservation, multimodal temporal alignment, and emergent complexity generation—provide solutions to fundamental challenges in causality modelling, temporal reasoning, and multi-agent coordination. We present current applications across game development, AI research breakthroughs, and cross-domain implementations, demonstrating gaming environments as controlled laboratories for developing robust AI capabilities. Our comprehensive data taxonomy spans 9 categories of game-generated information, from player telemetry to procedurally generated edge cases. Through analysis of gaming data integration with advanced architectures like Joint-Embedding Predictive Architecture (JEPA), we show how this resource addresses core limitations including representation collapse and planning constraints. The findings position gaming data as a critical complement to traditional datasets, enabling breakthrough applications in robotics, emergency response, economic modelling, and autonomous systems while providing natural supervision signals that traditional approaches struggle to capture.

Keywords: game-generated data, JEPA, multimodal learning, temporal reasoning, causality modelling, multi-agent systems, world models, behavioural analytics, emergent behaviour.

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1. The Current Landscape of AI Applications Trained With Gaming Data

The gaming industry has emerged as a pioneer in practical AI implementation, driving innovation across multiple domains that directly influence broader AI development. Game studios face unique challenges requiring real-time AI systems that must operate under strict computational constraints while delivering engaging, adaptive experiences to millions of users simultaneously. This environment has fostered breakthrough applications in AI-driven content generation [1, 2, 3], intelligent agent behaviour [4, 5], and automated quality assurance systems [6, 7].

This section presents current applications of gaming data for AI training across three critical domains that collectively demonstrate gaming's potential to overcome existing architectural limitations:

- **Direct game development applications** showcasing immediate practical implementations
- **Fundamental breakthroughs in AI research** including the Alpha series and world models

- **Cross-domain applications** demonstrating transfer to robotics, economics, and emergency response systems

These applications illustrate how gaming data's properties—including repeatability of scenarios, bounded action spaces, and multimodal temporal alignment—position it as a critical resource for advancing beyond current model limitations toward more capable AI systems with enhanced memory and hierarchical planning capabilities.

1.1 Game Development Applications

Gaming's demand for scalable, cost-effective AI solutions has led to developments that extend far beyond entertainment. The industry's need to generate vast amounts of content—from photorealistic environments using neural rendering techniques [8] to complex behavioural patterns—has accelerated advances in generative AI, while the requirement for intelligent, responsive non-player characters has pushed the boundaries of behavioural modelling [9, 10] and multi-agent coordination. Additionally, the scale and complexity of modern games necessitate sophisticated automated testing [11, 12] and security systems that leverage machine learning for quality assurance and anti-cheat detection [13].

These applications demonstrate how gaming data's natural characteristics—including real-time performance requirements, massive user bases, and diverse interaction patterns—drive AI innovations that subsequently transfer to robotics, autonomous systems, and other domains requiring robust, adaptive intelligence. Notable examples include NVIDIA's DLSS technology [14] demonstrating real-time video upscaling and AlphaStar's multi-agent coordination principles [4] transferring to broader AI applications.

Current state-of-the-art implementations span three critical areas:

- **Asset generation and procedural content creation** utilising GANs, diffusion models, and neural rendering techniques to automate game world creation
- **NPC development and behavioural AI** employing large language models and reinforcement learning to create adaptive, intelligent game characters
- **Testing, quality assurance, and security systems** leveraging machine learning for automated game testing, difficulty balancing, and anti-cheat detection

1.1.1 Asset Generation and Game Engines

AI-driven asset creation has transformed game development, enabling rapid and scalable generation of game worlds, characters, and environments. **Generative Adversarial Networks (GANs)** require domain-specific training data for asset types such as textures, models, animations, sounds, and terrain.[1, 3] For 3D asset creation, GANs can be combined with pixel2mesh techniques to generate 3D models from 2D images, enabling rapid prototyping without extensive manual modelling.[15, 16]

Diffusion models have emerged as state-of-the-art for high-fidelity texture synthesis [2], while **neural rendering techniques** such as Neural Radiance Fields (NeRF) enable photorealistic environments and multi-view geometry for immersive game worlds.[8] **NVIDIA's Deep Learning Super Sampling (DLSS)** exemplifies real-time application, using AI models trained on gameplay data to generate high-quality frames and boost performance.[14]

- **SOTA Models:** GANs, Diffusion Models, NeRF, DLSS
- **Data Requirements:** Images, 3D models, sound files, animations, terrain data, rendered frames

1.1.2 NPC Development and Behavioural AI

Large Language Models (LLMs) are increasingly used to generate engaging and context-aware NPC dialogue, enhancing player immersion and narrative depth.[9, 10] **Reinforcement Learning (RL)** enables NPCs to learn complex behaviours through self-play and player interaction data, creating adaptive opponents that evolve strategies over time.

Notable implementations include adaptive racing opponents in **Forza Motorsport** [5] and the grandmaster-level **AlphaStar** system for StarCraft II [4], which demonstrated sophisticated multi-agent coordination and long-term strategic planning capabilities that transfer to broader AI applications (see: **Section 1.2**).

- **SOTA Models:** LLMs for dialogue, RL for behavioural adaptation
- **Data Requirements:** Text corpora, dialogue scripts, player interaction logs, game states

1.1.3 Testing, Quality Assurance, and Anti-Cheat Systems

AI systems trained on game data automate critical development processes including **systematic testing**, **difficulty evaluation**, and **security monitoring**. By leveraging player traces and simulated gameplay, AI agents can explore game environments, identify bugs, and evaluate edge cases that human testers might miss.[11, 12]

Anti-cheat detection represents a sophisticated application where machine learning algorithms analyse player behaviour patterns, input sequences, and gameplay statistics to identify anomalies indicative of cheating software or automated scripts.[7, 13] **GlitchBench** demonstrates multimodal approaches using video footage and text descriptions to train LLMs for automated glitch detection.[6]

- **SOTA Models:** RL for testing, Anomaly Detection for anti-cheat, Multimodal LLMs for glitch detection
- **Data Requirements:** Player traces, game states, input patterns, video footage, labelled gameplay data

1.2 AI Research Breakthroughs

Gaming environments have emerged as research laboratories for fundamental AI research, enabling breakthroughs that extend far beyond entertainment to revolutionise scientific discovery, autonomous systems, and artificial general intelligence development. The bounded yet complex nature of game worlds provides controlled experimental conditions where AI systems can be tested, refined, and scaled before deployment in real-world applications where failure carries significant consequences.

The foundational role of gaming in AI research was established through DeepMind's groundbreaking work with the Atari 2600 games.[17] The Deep Q-Network (DQN) achieved human-level performance across 49 Atari games using only raw pixel inputs and game scores as rewards, demonstrating for the first time that a single architecture could master diverse tasks without game-specific engineering. This work proved that deep reinforcement learning could learn directly from high-dimensional sensory inputs, establishing gaming as a critical benchmark for general AI capabilities.

The progression from game-specific AI to general-purpose breakthroughs demonstrates gaming's role as a critical stepping stone toward artificial general intelligence. Recent advances in multimodal diffusion models for playable world generation [18, 19] and generalist agents that can understand diverse 3D environments[20] illustrate how gaming data's natural multimodal alignment creates more robust AI architectures with enhanced data efficiency through imitation learning techniques.[21, 22]

These research breakthroughs span three foundational areas that collectively demonstrate gaming's unique contribution to advancing AI capabilities:

- **The Alpha series progression** from game mastery to scientific discovery, demonstrating how gaming AI principles enable breakthroughs in protein folding and competitive programming
- **World models and multimodal systems** leveraging gaming's natural temporal and causal structure to develop AI systems that understand environmental dynamics and simulate future states
- **Multi-agent systems and emergent behaviour** utilising gaming's competitive and cooperative scenarios to develop AI capable of complex coordination and adaptive strategy formation

1.2.1 The Alpha Series: From Games to Scientific Discovery

The **Alpha series** of models from DeepMind represents a significant demonstration of how gaming AI drives broader scientific advancement.[23] **AlphaGo** first achieved superhuman performance in Go using human expert game records combined with self-play, establishing the foundation for subsequent breakthroughs. This lead to **AlphaZero**, a generalised approach for learning Chess, Shogi, and Go from scratch through pure self-play, demonstrating domain-agnostic learning principles.[24] This research directly lead to **AlphaFold** [25], which solved the 50-year-old protein folding problem, and **AlphaCode** [26], achieving human-level performance in competitive programming.

This progression illustrates how gaming environments have already served as controlled laboratories for developing AI techniques that subsequently revolutionise scientific fields.

1.2.2 World Models and Multimodal Systems

Gaming data has become instrumental in developing **world models**—AI systems that understand environmental dynamics and can simulate future states.[27] Recent advances include **multimodal diffusion models** that generate playable game worlds from text prompts, such as **SORA** [18], **GameGen-X** [19], and Google's latest **Genie 3** [28, 29], which enables real-time interaction at 24 frames per second with consistent environments lasting several minutes. Besides, recent work on **Dynamic World Simulation (DWS)** demonstrates how pre-trained video generative models can be transformed into controllable world simulators capable of executing specified action trajectories, achieving significant improvements in action-controllable video generation across games and robotics domains [30].

Google's SIMA represents a breakthrough in generalist AI agents that can understand and interact with diverse 3D environments, trained across multiple gaming platforms to develop transferable skills for real-world applications.[20]

These systems leverage gaming's natural alignment between visual, audio, and action modalities to create more robust multimodal AI architectures with improved data efficiency through **imitation learning** techniques.[21, 22] This natural multimodal alignment becomes crucial for JEPA integration, discussed in **Section 4**.

- **SOTA Models:** World Models, Multimodal Diffusion Models, Imitation Learning
- **Data Requirements:** Text prompts, video footage, multi-view images, action sequences

1.2.3 Multi-Agent Systems and Emergent Behaviour

Gaming environments generate rich "*in-the-wild*" data on **multi-agent interactions** that current AI systems struggle to model effectively, providing unique training opportunities for developing sophisticated coordination and emergent behaviour capabilities. The competitive and cooperative nature of games creates ideal laboratories for studying complex multi-agent dynamics that extend far beyond entertainment applications. As demonstrated in previous AI breakthroughs (**Section 1.2**), gaming environments have proven invaluable for training AI systems on complex multi-agent interactions, leading to significant advancements in autonomous systems and artificial general intelligence.

Emergent Strategy Development: OpenAI's hide-and-seek experiments revealed six distinct emergent strategies, including unexpected physics exploits like "*box surfing*," demonstrating how competitive gaming scenarios create organic auto-curricula for AI development [11]. These emergent behaviours showcase the kind of creative problem-solving and adaptive strategy formation that traditional training datasets cannot capture, where agents develop increasingly sophisticated counter-strategies through competitive pressure.

Massively Multiplayer Coordination: Massively multiplayer games provide unprecedented datasets on cooperation, competition, deception, and trust formation across thousands of simultaneous agents [31, 32]. These environments enable training of AI systems that can coordinate in complex, dynamic scenarios with multiple competing objectives, addressing critical gaps in current AI's ability to understand and predict multi-agent behaviours [33, 34].

Emergent Auto-Curricula Generation: Gaming environments create auto-curricula [35] where players develop increasingly sophisticated counter-strategies, providing training data for adaptive AI systems that must respond to evolving adversarial behaviours. This addresses the limitations in current training approaches where exponential increases in training data yield only linear performance improvements [36] by providing diverse, high-quality examples of strategic adaptation and emergent coordination.

1.3 Cross-Domain Applications

Video game environments have emerged as powerful training grounds for AI systems that now operate robots in warehouses, guide surgeons through complex procedures, optimise city traffic flows, and reduce agricultural chemical usage by up to 90%.

The breakthrough lies in transfer learning—the ability to train AI models in safe, controlled gaming environments and then deploy them in high-stakes real-world scenarios. **NVIDIA's Isaac Sim platform** [37] demonstrates this with zero-shot transfer from simulation to real robots performing complex gear assembly tasks, while **Covariant's warehouse robotics** [38] operate across 300+ facilities in 15 countries, handling millions of successful picks. The technology has matured from research curiosity to production-ready systems generating measurable ROI, with Amazon reporting that a mere 1% supply chain improvement translates to **$1 billion in annual savings** [39].

Gaming engines like Unity and Unreal Engine have become the unexpected backbone of this transformation. Originally designed for entertainment, these platforms now power **surgical training systems that improve performance by 230-300%** [40], military simulations training 500,000+ personnel annually [41], and climate models engaging 347,000 participants across 165 countries [42]. The economics are compelling: what once required custom million-dollar simulators can now be developed using commercial game engines at a fraction of the cost, democratising access to advanced AI training capabilities.

1.3.1 Robotics and Manufacturing Achieve Zero-Shot Deployment

The robotics revolution promised for decades has finally arrived through game-based training environments. **NVIDIA's Isaac Sim platform** [37], built on Omniverse and Unreal Engine architecture, enables robots to learn complex assembly tasks in simulation and execute them perfectly in the real world without additional training—a capability called zero-shot sim-to-real transfer.

Universal Robots demonstrated this breakthrough in 2024-2025 with their UR10e robot successfully performing gear assembly tasks after training entirely in Isaac Lab's simulated environments. The system uses domain randomisation—varying physics parameters, lighting conditions, and object properties during training—to create robust models that generalise to real-world variability. Companies including Field AI, Vention, Swiss Mile, and Standard Bots have deployed similar systems across construction sites, warehouses, and manufacturing floors.

Covariant's Robotics Foundation Model (RFM-1) [38] represents the scale achievable with this approach. Their 8-billion parameter model, trained on 50+ million warehouse manipulation episodes, powers 300+ robots across 15 countries. The company reported **6x growth in deployments between 2022-2023**, with major customers including Radial Inc. operating 12 AI-powered robotic putwalls. Amazon's recent acquisition of Covariant in 2025 signals the strategic importance of these capabilities.

Unity ML-Agents proved game environments can train sophisticated behaviours through Ghelia Inc.'s soccer-playing robots [43]. After training in Unity's soccer simulation for approximately 3 days per iteration, Sony toio robots successfully played 4v4 soccer matches in the real world. The project used clever adaptations like golf balls for physics matching and OpenCV for vision processing, demonstrating that even consumer-grade robotics can benefit from game-based training.

DeepMind advanced humanoid robotics significantly with their 2024 publication in Science Robotics [44] showing OP3 humanoid robots playing soccer after training in custom MuJoCo environments. Their new Gemini 2.0-based robotics models work with ALOHA 2 bi-arm platforms and Apptronik's Apollo humanoid, bringing vision-language-action capabilities to physical manipulation tasks. Boston Dynamics integrated NVIDIA Isaac Lab for training their Atlas humanoid [45], partnering with the Robotics & AI Institute to develop dynamic behaviours through parallel simulation.

1.3.2 Medical Breakthroughs Emerge from Gaming Crossovers

Surgical training underwent a paradigm shift as game developers brought their expertise to medical simulation. **Level Ex** [46], founded by Emmy Award-winning DirectX team leader Sam Glassenberg with executives from Electronic Arts, created mobile surgical apps used by **3 million users including 800,000 medical professionals earning CME credits**. Stanford University Medical School pre-installs their Airway Ex app on all student iPads, while sales teams using their VR platform saw 6% lift in sales and 65%

increase in conversions.

Osso VR's impact proves particularly striking with UCLA studies showing **230-300% improvement in surgical performance** [40] compared to traditional training methods. Their platform enables surgeons to complete procedures **25% faster** after VR training, with the Journal of Bone and Joint Surgery reporting **570% faster learning** compared to conventional approaches. Eight peer-reviewed studies validate these results, leading to adoption at Johns Hopkins, UCLA, Harvard, and Community Memorial Health System. The platform trains 3,000-5,000 professionals monthly across 300+ training modules in over 40 countries.

PrecisionOS [47] leveraged Unreal Engine's capabilities for orthopaedic surgery training, achieving similar **570% faster training** results published in the Journal of Bone and Joint Surgery. Founded by former game developers from United Front Games and Electronic Arts, they deployed Oculus Quest headsets to 365 hospitals in 53 countries through partnership with SIGN Fracture Care, eliminating travel costs for surgical education in developing nations.

Game engines themselves became critical medical infrastructure. Unity powers VirtaMed's LaparoS surgical simulator [48] and Cincinnati Children's Hospital's VR3S suite for patient-specific cardiac surgery planning. Unreal Engine enables University of Tokyo's brain surgery simulation with real-time deformation at 40-50 frames per second, visualising patient-specific anatomy from MRI data. The FDA has approved multiple gaming-derived medical devices, including AppliedVR's RelieVRx for chronic lower back pain [49] and PrecisionOS's InVisionOS platform.

1.3.3 Cities Optimise Operations Through Game-Trained Intelligence

Urban infrastructure management transformed as game-trained AI tackled traffic optimisation and city planning challenges. **DeepMind's Graph Neural Networks** [50], integrated into Google Maps, serve over 1 billion users with **up to 50% reduction in ETA prediction errors** and **97% accuracy for trip predictions globally**. The system treats road networks as graphs similar to game environments, with particularly impressive 50% improvements in cities like Taichung.

Waymo's SimulationCity [51] demonstrates the power of game-inspired virtual worlds for autonomous vehicle development. Named after World of Warcraft (evolving from their earlier Carcraft system), the platform runs 25,000+ virtual self-driving cars that have accumulated **20+ billion miles in simulation**. This virtual training enables Waymo's fleet to achieve 20+ million real-world autonomous miles, with **80% of algorithmic improvements now originating from simulation** rather than real-world testing. The system processes 8 million virtual miles daily, equivalent to 2.5 billion miles annually.

UrbanSim's AI platform [52] impacts **81.8 million people across 5 continents** through AI-driven urban planning that integrates land use, transportation, economy, and environmental modelling. The platform has generated over 10,000 academic citations and helps cities make data-driven development decisions. Singapore's digital twin project [53], launched in 2014 using Cities: Skylines technology, represents what officials call "*the future of how we manage our city.*"

The Digital Twin Cities Centre in Sweden partnered with Epic Games [54], receiving an $80,000 Mega Grant to develop automated 3D city model generation using Unreal Engine. Their DTCC Builder combines with commercial game engines for procedural city generation with real-time sensor data integration, enabling heat maps, streamlines, and volume rendering for scientific visualisation.

Climate modelling benefited significantly from game-based approaches. textbfEn-ROADS and C-ROADS simulators [42] by Climate Interactive and MIT Sloan engaged **347,000+ people across 165 countries**, training 130+ US Congress members and 920+ Climate Ambassadors globally. The systems helped facilitate 465,000+ participants in climate workshops across 181 countries, using game-like interfaces to make complex climate modelling accessible to policymakers.

1.3.4 Military and Emergency Response Accelerate Preparedness

Defence organisations embraced commercial game technology for training and operational planning. **DARPA's Gamebreaker programme** [55] (2020-2025) used StarCraft and other strategy games to develop AI algorithms identifying imbalanced conditions in military simulations. Northrop Grumman's $1 million contract produced methodologies for assessing game balance transferable to military planning scenarios.

Virtual Battlespace (VBS4) [41] integrated with Unreal Engine and Unity trains **over 500,000 military personnel annually** across 60+ NATO countries. The platform involves 250+ integrators and prime contractors, with VBS World Server streaming whole-Earth terrain data to enable correlated multi-engine simulation environments. Lockheed Martin's long-term partnership with Epic Games [56], initiated in 2022, creates unified training environments replacing previously isolated platform-specific simulators with photo-realistic visuals that improve training effectiveness while reducing development costs.

Emergency management systems achieved dramatic improvements through game-based training. **Texas A&M's CLARKE system** [57] reduced damage assessment time **from weeks to minutes** using AI trained on 21,000+ house images across 10 major disasters. Over 60 emergency responders from 38 agencies received training in 2025, with the National Science Foundation and AI Institute for Societal Decision-Making supporting continued development.

George Mason University's **Go-Repair and Go-Rescue games** [58] provide stress-free training environments for utility managers and emergency responders, with AI optimisation and RL models offering real-time feedback on decision quality. Named finalist in the 2024 IISE Data Analytics Competition, the system helps Arlington County Emergency Management and other agencies prepare for hurricanes and infrastructure restoration scenarios.

NATO's AI strategy implementation [59] (2021-2025) incorporates AI-augmented wargaming and strategic scenario simulation across the alliance. The AI FELIX digital assistant achieved **80% reduction in document processing time**, while integration with Ukraine and Georgia in pilot AI training projects demonstrates international cooperation potential. NASA's Robotic Search and Rescue Challenge [60] teaches disaster response through programmable robotic platforms, with JavaScript and block programming enabling students to develop UAV solutions for emergency scenarios.

1.3.5 Financial Markets Embrace Gaming Algorithms

The quantitative finance revolution accelerated as game-trained AI models proved superior to traditional approaches. **Deep Reinforcement Learning algorithms** [61], originally developed for games like AlphaGo, consistently outperform mean-variance optimisation methods by **6-8% in both Vietnamese and U.S. securities markets**. These same algorithms that mastered complex games now navigate financial markets with superior risk-adjusted returns.

Major quantitative trading firms lead adoption. **Two Sigma** [62] manages \$60+ billion with 1,500+ employees focused heavily on RL applications. **Renaissance Technologies** [63] maintains the secretive Medallion Fund charging 5% management plus 44% performance fees, justified by exceptional returns from AI-driven strategies. Jane Street [64] emphasises deep learning as "*the future of quantitative trading*," applying collaborative problem-solving approaches using advanced AI originally developed for gaming contexts.

Supply chain optimisation achieved remarkable results through game-based training. **Amazon's Deep Inventory Management (DIM)** [39] system, published in 2022 and implemented across 10,000+ SKUs, uses deep RL for multi-product, multi-fulfilment centre optimisation. The company's broader automation initiative includes **750,000+ robots** [65] across their operations network, achieving **15% reduction in recordable incident rates** and **18% reduction in lost-time incidents** at robotics sites while creating 700 new job categories.

The Beer Game, a classic supply chain simulation, became a proving ground for AI coordination [66]. Modified Deep Q-Networks achieved performance within **2-8% of optimal base-stock policies** while using transfer learning for **15x faster training** (891,117 vs 13,354,951 seconds). When playing with irrational human players, DQN achieved **40% smaller costs** than traditional approaches, demonstrating robustness to real-world complexity.

UPS's ORION system [67] saves **38 million litres of fuel annually** while preventing **100,000 metric tonnes of CO2 emissions yearly**. Processing 30,000 route optimisations per minute and analysing 250+ million address data points daily, the system exemplifies how game-like pathfinding algorithms scale to global logistics networks.

FedEx [68] achieved similar results with robotic arms sorting 1,000-1,600 packages per hour and AI-powered predictive maintenance saving $11 million annually.

1.3.6 Education Transforms Through Game-Based Learning

Educational technology experienced a renaissance as game-trained AI personalised learning at scale. **UC Berkeley's Open Adaptive Tutor (OATutor)** [69] achieved **learning gains equivalent to human tutors** using ChatGPT-generated hints screened by domain experts. The platform won $150,000 as finalist in the 2023-24 Tools Competition and received a $50,000 microgrant for expansion, with Associate Professor Zachary Pardos demonstrating statistically insignificant differences between human and AI-generated hints.

Major educational platforms integrated game-trained models rapidly. **Carnegie Learning's LiveHint AI** [70] leverages 5.5 million students' data from 1.2 billion maths problems over 25 years. Khan Academy's Khanmigo [71] provides personalised tutoring using AI-powered feedback adapted from game-like interaction patterns. Unity ML-Agents [72] teaches high school students AI fundamentals through spatial search tasks and interactive tutorials with immediate feedback.

London Metropolitan University integrated OpenAI tools into game programming education [73], with students evaluating AI assistance for Unity-based prototype development during the 2022-2023 academic year. The National Academy for AI Instruction [74] launched with $23 million funding to scale these approaches, while ChatGPT Edu rollout brings game-trained educational AI to universities globally.

1.3.7 Agriculture Achieves Precision Through Gaming Technology

Agricultural technology underwent dramatic transformation as game-trained computer vision revolutionised farming practices. **John Deere's "See and Spray" system** [75], developed by Blue River Technology (acquired for $305 million in 2017), achieves **up to 90% reduction in herbicide usage** through precision application. The system processes images every 50 milliseconds at 7 mph tractor speed using 30 cameras covering 40-foot wide, 12-row coverage powered by 25 Jetson AGX Xavier supercomputing modules per machine. Field testing demonstrated **77% herbicide reduction** with potential to eliminate 2.5 billion pounds of chemicals annually from global agriculture. The deep learning algorithms, trained on hundreds of thousands of labelled images distinguishing weeds from crops, represent a direct transfer of gaming computer vision techniques to agricultural applications. NVIDIA GPU acceleration enables real-time plant identification and targeted spraying that would be impossible with traditional approaches.

FarmBot's precision agriculture platform [76] brings gaming mechanics directly to farming through their Farmville-like web interface. Over 500 educational institutions use FarmBot for teaching precision agriculture, with 18m^2 field deployments achieving $1mx1m$ plot precision using CNC technology with sub-millimetre accuracy. The open-source platform built on Raspberry Pi and Arduino enables global collaboration, with NASA incorporating the technology for space agriculture research.

Virtual Reality transforms agricultural training through John Deere's harvester and forwarder simulators, providing risk-free training environments with significant cost savings over traditional methods. Unity ML-Agents enables autonomous navigation for farm equipment, robotic crop monitoring, and multi-agent coordination for farm operations through simulation-to-reality transfer and curriculum learning approaches.

The AgriNet Dataset [77] demonstrates successful domain adaptation with 160,000 agricultural images for crop disease, pest, and weed detection. VGG16 models with PlantVillage weights achieve **60.42% accuracy versus 44.52% with ImageNet weights**, while ResNet50 reaches **97% accuracy for apple disease detection**. These results prove that game-trained vision models can be effectively adapted to agricultural challenges through careful transfer learning.

The AgriNet Dataset [77] demonstrates successful domain adaptation with 160,000 agricultural images across 423 classes for crop disease, pest, and weed detection. When evaluated on external datasets, VGG16 models with AgriNet weights achieve **90% accuracy versus 83% with ImageNet weights** on a rice pest and disease dataset, and **83% accuracy versus 70% with ImageNet weights** on a Kashmir plant disease dataset. The AgriNet-VGG19 model reaches **94% test accuracy** on the full AgriNet dataset with an F1-score of 92%. These results prove that agriculture-domain-specific pretrained models significantly outperform general ImageNet models when adapted to agricultural challenges through transfer learning.

1.3.8 Transformative Economics Drive Adoption

The economic impact of game-trained AI deployment proves compelling across all sectors. Amazon's 1% supply chain improvement generates $1 billion in annual savings [39], while UPS saves 38 million litres of fuel yearly through route optimisation [67]. Medical institutions report 230-300% performance improvements with 570% faster training [40], reducing costs while improving outcomes. Agricultural applications achieve up to 90% reduction in chemical usage [75], potentially eliminating 2.5 billion pounds of herbicides globally.

Development costs plummeted as commercial game engines replaced custom simulators. What previously required millions in specialised development now leverages Unity or Unreal Engine at a fraction of the cost. VR surgical training eliminates travel expenses for medical education, while military organisations replace expensive custom simulators with commercial game technology. The democratisation of AI training capabilities enables smaller organisations to compete with established players.

Time-to-deployment accelerated dramatically through transfer learning. Beer Game AI achieved 15x faster training through transfer learning [66], while zero-shot sim-to-real enables immediate deployment without real-world training. CLARKE's disaster assessment reduced response time from weeks to minutes [57], and game-based climate models engaged 465,000+ workshop participants in record time [42]. The ability to iterate quickly in safe virtual environments before real-world deployment reduces both risk and development cycles.

1.3.9 Future Trajectories Point Toward Convergence

The convergence of gaming technology with real-world applications accelerates as foundation models scale. Covariant's 8-billion parameter robotics model [38] and DeepMind's Gemini 2.0 robotics platform signal a shift toward general-purpose systems trained across multiple domains. The "*ChatGPT moment*" for robotics, predicted for 2025-2030 [78, 79], appears imminent as game-to-real transfer technologies demonstrate commercial viability.

Edge computing enables real-time deployment in resource-constrained environments, from agricultural fields to disaster zones. Federated learning allows collaborative training across institutions while preserving privacy, and multimodal AI integrates vision, language, and sensor data originally developed for gaming contexts. Quantum computing promises to accelerate optimisation problems currently limiting supply chain and financial applications.

Standardisation efforts gain momentum as the field matures. Common frameworks for evaluating transfer learning effectiveness emerge from academic conferences, while regulatory bodies develop guidelines for game-trained AI in critical applications. Industry consortiums form around shared simulation platforms, and open-source initiatives democratise access to advanced capabilities. The transformation from gaming entertainment to mission-critical infrastructure represents one of the most significant technology transfers of the digital age, with measurable benefits across every sector examined and clear trajectories toward even broader adoption in the years ahead.

2. Gaming Data's Untapped Potential for AI Systems

Gaming data represents one of the most underutilised opportunities for AI advancement, offering unique characteristics that directly address critical limitations plaguing current AI systems. While the industry faces an imminent data crisis, gaming platforms generate terabytes of rich behavioural data daily that remains largely untapped for AI training.

This section explores critical gaps in current training data (**Section 2.1**) and demonstrates how gaming data uniquely addresses these challenges through its distinctive characteristics (**Section 2.2**). We examine the technical advantages gaming environments provide—from causal relationship preservation to multimodal data alignment—that directly resolve limitations in temporal reasoning, behavioural complexity modelling, and edge case coverage that plague traditional datasets. We identified breakthrough applications (**Section 1.2**) emerging at the intersection of gaming and AI, showcasing how these unique data properties enable novel capabilities in robotics, emergency response, economic modelling, and adaptive educational systems. Finally, we demonstrate how gaming data complements rather than replaces existing sources (**Section 2.2**), providing a practical framework for integrating these resources into current AI training pipelines.

2.1 Critical Gaps in Current AI Training Data

The AI industry faces a convergence of data constraints that threaten continued progress across three critical dimensions that gaming data is uniquely positioned to address. These fundamental limitations span quantity scarcity (**Section 2.1.1**), quality and coverage deficiencies (**Section 2.1.2**), and technical inadequacies in capturing the complex temporal, causal, and behavioural patterns essential for robust AI systems. Understanding these gaps provides the foundation for appreciating how gaming environments naturally generate the precise types of data that current AI training approaches desperately need.

2.1.1 Data Quantity Crisis

High-quality text data will be exhausted between 2026-2032, with 50% of websites already implementing data restrictions.[80, 81] This scarcity problem extends beyond volume to diversity, with robotics applications suffering from expensive, limited real-world interaction data,[82] while medical AI faces severe constraints from small clinical trials and privacy regulations.[83, 84] Most critically, **exponential increases in training data yield only linear performance improvements**[36] on novel scenarios, indicating fundamental inefficiencies in current data utilisation approaches.

2.1.2 Quality and Coverage Limitations

Modern internet-based datasets suffer from fundamental quality issues that compromise AI system reliability. DataComp CommonPool, a major open-source dataset with 12.8 billion samples, contains millions of privacy violations including 800+ identity documents and 102 million unblurred faces.[85] Beyond privacy concerns, traditional datasets exhibit severe limitations in capturing real-world complexity and fail catastrophically at covering edge cases and emergent behaviors essential for robust AI systems.

Traditional training data exhibits critical technical deficiencies that directly impact AI capability development:

- **Temporal Reasoning Deficits**: Models excel at detecting temporal cues but fail at multi-step temporal reasoning, struggling with decision chains that cascade through multiple time steps. Current datasets provide primarily static snapshots rather than the continuous behavioural streams necessary for understanding temporal causality.[33]

- **Behavioural Complexity Gaps**: Theory of Mind capabilities remain superficial—AI can answer questions about mental states but cannot apply this knowledge to predict human behaviors or understand multi-agent interactions [34]. Traditional datasets fail to capture the emergent complexity arising from multi-agent interactions and creative problem-solving strategies.

These deficiencies are precisely what **gaming data can address** through its unique characteristics.

2.2 Gaming Data Addresses Critical Gaps in Current AI Training

Gaming environments naturally generate the exact types of data that current AI systems desperately need, offering unique advantages across behavioural complexity, technical capabilities, and practical implementation that traditional datasets cannot match.

2.2.1 Technical Advantages and Data Quality

Causal Relationship Preservation and Physics Understanding: Gaming environments provide a fundamental advantage over traditional training data by enforcing consistent physics laws and logical consequences. Unlike neural networks trained on static datasets that treat physics laws as learnable patterns rather than inviolable constraints [86, 87, 88, 89], game engines ensure that actions have bounded, predictable consequences, providing training data where causality is preserved rather than approximated.

This addresses critical limitations in current AI systems where models excel at detecting temporal cues but fail at multi-step temporal reasoning, struggling with decision chains that cascade through multiple time steps. Gaming environments capture creative physics exploitation ("*glitches*")—using unintended mechanics to solve problems — demonstrating the kind of innovative exploitive thinking AI systems need for real-world problem-solving.[90] Unlike static physics datasets, games generate continuous streams of cause-and-effect relationships where player actions have immediate, observable consequences, providing the temporal richness necessary for understanding temporal causality.

Procedurally generated content creates natural edge case coverage that addresses the long-tail problem plaguing current AI training approaches. No Man's Sky's 18 quintillion planets and Minecraft's infinite worlds generate scenarios never explicitly programmed, stress-testing player adaptability and generating rare event coverage that would require exponential data collection through traditional methods.[1, 3, 91] This procedural generation ensures comprehensive scenario coverage without the manual curation costs that limit traditional datasets.

Multimodal data alignment occurs naturally in gaming environments where visual, audio, and action modalities are inherently synchronised by the game engine. Unlike traditional datasets that require expensive post-hoc alignment or labelling, gaming data provides perfect temporal correspondence between what players see, hear, and do. This natural alignment is crucial for training robust multimodal AI systems that must integrate information across sensory channels.[21, 22, 92]

Causal relationship preservation represents a fundamental advantage over current training data. Gaming environments enforce consistent physics laws and logical consequences, addressing the critical limitation where neural networks treat physics as learnable patterns rather than inviolable constraints.[86, 87, 88, 89] Game engines ensure that actions have predictable consequences, providing training data where causality is preserved rather than approximated.

2.2.2 Practical Benefits and Implementation Advantages

Scalability and cost-effectiveness distinguish gaming data from traditional collection methods. While robotics applications suffer from expensive, limited real-world interaction data [82] and medical AI faces constraints from small clinical trials [83, 84], gaming platforms generate terabytes of rich behavioural data daily at minimal marginal cost. This scalability addresses the fundamental bottleneck where exponential increases in training data yield only linear performance improvements [36] by providing diverse, high-quality examples rather than simply more volume.

Natural supervision signals eliminate the need for expensive manual annotation that limits traditional dataset development. Gaming environments provide implicit feedback through player engagement metrics, explicit choices through game mechanics, and objective outcomes through win/loss conditions. These natural preference signals enable training AI systems that align with human values and decision-making patterns without requiring extensive human labeling efforts.

Controllable experimental conditions enable systematic AI research that would be impossible with real-world data collection. Game engines allow precise manipulation of variables to study specific phenomena while maintaining perfect ground truth labels.[93, 94] This controllability is particularly valuable for safety-critical applications where real-world experimentation would be dangerous or unethical.

Complementary integration with existing approaches ensures that gaming data enhances rather than replaces current training methodologies. Cross-modal pre-training using gaming's natural alignment between visual, audio, and action modalities can enhance vision-language models by adding temporal and causal dimensions that traditional datasets lack. Gaming environments serve as controllable laboratories for systematic AI research, generating unlimited variations of training scenarios that complement real-world datasets.[95]

This comprehensive suite of advantages positions gaming data as a critical resource for addressing fundamental limitations in current AI training approaches, particularly in areas of causality modelling, temporal reasoning, multi-agent interactions, and real-world constraint handling that traditional datasets struggle to capture effectively. Furthermore, video games have become a common benchmark for evaluating AI agents, from traditional games such as chess and go [23, 24] to modern real-time gaming environments requiring planning and multi-agent dynamics. [96, 97, 98, 99, 4, 100] It is clear that video game data is a critical resource for advancing AI towards these goals.

3. Data Sources and Taxonomy

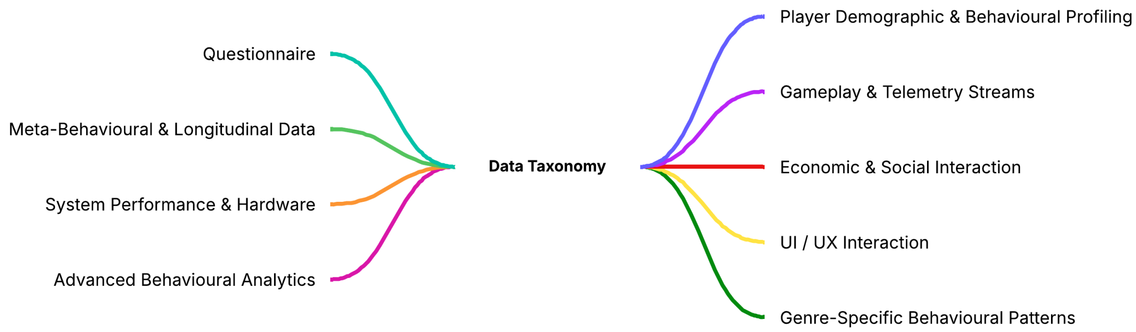

Figure 1: Gaming Data Taxonomy

3.1 Comprehensive Gaming Data Infrastructure

This project leverages an extensive taxonomy of game-generated data organised into 9 distinct categories, each capturing unique aspects of human behaviour and decision-making within gaming environments. The data infrastructure spans multiple platforms (mobile, console, PC) and genres (RPG, MMO, puzzle, strategy), generating vast amounts of multimodal data that addresses critical gaps in current AI training datasets.

3.2 Data Categories and Characteristics

3.2.1 Primary Data Categories

Player Demographic and Behavioural Profiling Our dataset encompasses comprehensive player demographic data including regional distribution, customisation preferences, and behavioural archetypes derived through analytical frameworks. This includes player skill classifications through Elo rating systems and tier-based rankings (bronze/silver/gold/diamond), providing stratified samples across skill levels. Behavioural archetype classification identifies explorers, achievers, socialisers, and competitors, enabling targeted analysis of decision-making patterns across different player motivations.

Gameplay and Telemetry Streams The core of our dataset consists of high-resolution gameplay telemetry including complete session recordings, player movement coordinates, action sequences, and real-time game state information. This encompasses granular input data (shooting, jumping, reloading, crafting actions), session metrics (playtime, attention span indicators), and comprehensive event logs tracking level completions, boss encounters, item collections, and story progression milestones. Resource allocation and expenditure patterns provide insights into economic decision-making under constraints.

Advanced Behavioural Analytics Our behavioural data captures choice tracking across dialogue options, quest decisions, and strategic planning sequences. Exploration patterns distinguish between exploitation versus exploration tendencies in open-world environments, while fail/retry patterns reveal learning curves and adaptation strategies. Time-to-completion metrics and strategy detection algorithms identify long-term planning behaviours and preferred play styles.

Economic and Social Interaction Data The dataset includes comprehensive in-game economic data covering item browsing histories, acquisition sequences, spending patterns, and inventory management strategies. Social interaction data encompasses chat logs, player-versus-player interactions, friendship networks, clan dynamics, and matchmaking metrics. Cooperation patterns and team play preferences provide insights into multi-agent coordination and social decision-making.

3.2.2 Technical and Performance Metrics

System Performance and Hardware Analytics Technical data includes device specifications across mobile, console, and PC platforms, performance metrics (frame rates, loading times), crash reports, and network latency measurements. This data enables analysis of how technical constraints influence player behaviour and decision-making patterns.

User Interface and Experience Data UI/UX interaction data captures menu navigation patterns, button click sequences, view engagement metrics, and interface exploration behaviours. Heat map data and interaction funnels reveal usability patterns and attention distribution across game interfaces.

3.2.3 Specialised Data Streams

Genre-Specific Behavioural Patterns The dataset includes genre-specific data patterns tailored to different game types:

- **Role-Playing Games (RPGs)**: Role-playing character control and strategic choices
- **Massively Multiplayer Online (MMO) Games**: Collaboration versus competition dynamics
- **Puzzle Games**: Strategic thinking patterns in puzzle games
- **Virtual/Augmented Reality (VR/AR) Experiences**: Physical-world interaction data
- **Open-World Games**: Exploration versus main storyline focus

Meta-Behavioural and Longitudinal Data Meta-behavioural data captures login frequency patterns, churn prediction indicators, platform migration behaviours, and extended data beyond direct gameplay interactions. This longitudinal data enables analysis of long-term behavioural evolution and adaptation patterns.

3.3 Direct Survey Integration

Targeted Questionnaire Data The dataset is enhanced through large-scale in-game questionnaire systems delivered in partnership with popular game titles. Current implementations include climate change attitudes and nature conservation surveys through the Play2Act initiative, with capabilities for exploring lifestyle choices, financial behaviours, and other topics relevant to AI training objectives.

3.4 Data Quality and Scale Characteristics

The gaming data infrastructure provides several critical advantages over traditional AI training datasets:

- **Temporal richness**: Continuous behavioural streams rather than static snapshots
- **Causal relationships**: Clear cause-and-effect patterns through player actions and consequences
- **Edge case coverage**: Natural generation of rare scenarios through procedural content and emergent gameplay
- **Multimodal alignment**: Natural correlation between visual, audio, and action modalities
- **Human preference signals**: Implicit feedback through engagement metrics and player choices

This comprehensive data taxonomy addresses fundamental limitations in current AI training approaches, particularly in areas of causality modelling [86, 87, 88, 89], temporal reasoning [33], multi-agent interactions [32, 11], and real-world constraint handling [101, 102]. All areas which traditional datasets and benchmarks struggle to capture human reasoning, behaviours, and preferences effectively.

4. Joint-Embedding Predictive Architecture (JEPA) Model Overview

The Joint-Embedding Predictive Architecture (JEPA) represents a major advancement in AI model design, focusing on learning robust representations by predicting future states in a joint-embedding space. Unlike traditional supervised or autoregressive models, JEPA leverages self-supervised objectives to capture the underlying structure and dynamics of complex environments, enabling more effective generalisation, planning, and causal reasoning.

JEPA models operate by encoding both context and target data into a shared latent space, optimising the architecture to predict the target embedding from the context. This approach allows the model to learn abstract, temporally aligned representations that are resilient to noise and capable of capturing long-term dependencies. Recent advances, such as V-JEPA2 and M3JEPA, demonstrate state-of-the-art performance in multimodal prediction tasks, including video, audio, and sensor data, with applications ranging from robotics and autonomous systems to gaming and simulation environments [103, 104, 105].

A key advantage of JEPA is its ability to address core limitations in current AI systems, such as representation collapse, poor planning horizons, and limited causal understanding. By leveraging game-generated data, JEPA models benefit from naturally occurring supervision signals, multimodal temporal alignment, and diverse behavioural scenarios, further enhancing their capacity for hierarchical reasoning and emergent behaviour discovery.

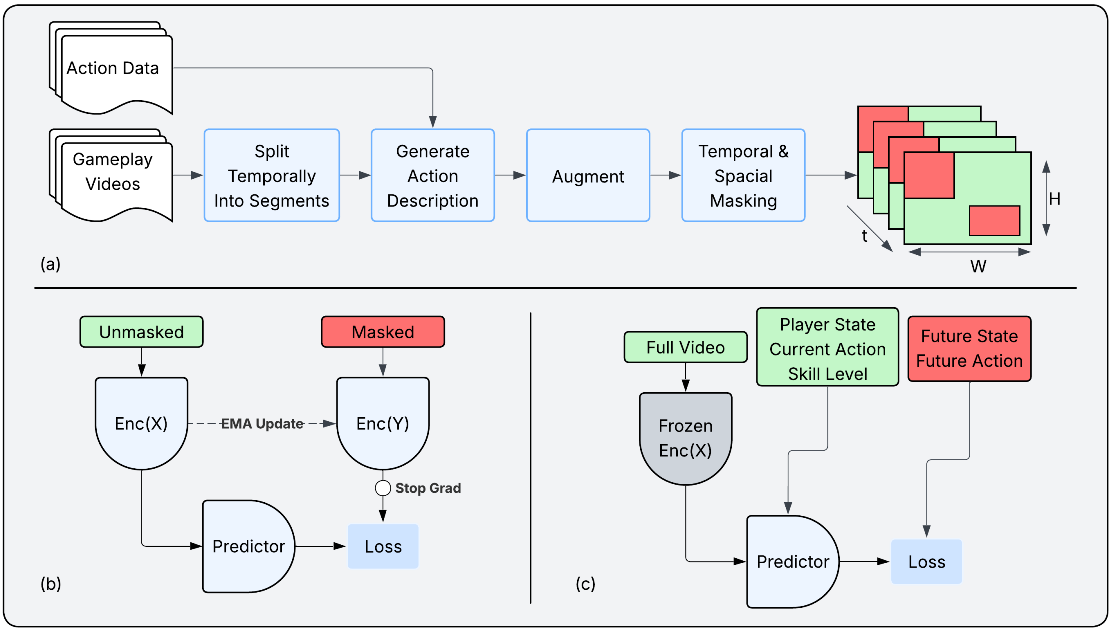

Figure 2: (a) Video data preprocessing pipeline for collecting and aligning player actions with video frames. (b) Overview of the V-JEPA2 model self-supervised architecture, including the encoder, predictor, and EMA encoder components. (c) Downstream task training using the joint embeddings to predict player actions and game states.

This section provides an in-depth overview of JEPA's architecture, training objectives, and integration with gaming data, highlighting its transformative potential for next-generation AI systems.

4.1 JEPA Architecture

The Joint-Embedding Predictive Architecture (JEPA) is a self-supervised learning framework designed to learn world models from multiple data sources, including video, text, and audio. These inputs are all represented in a single joint embedding space, allowing the model to learn complex relationships between different modalities. The architecture is inspired by neuroscience, composing of modules that mimic the human brain's ability to process, predict and act on sensory information. The architecture is inspired by theories from computational neuroscience and cognitive science, particularly predictive coding and hierarchical predictive processing frameworks [106, 107, 108]. It comprises modules that parallel the brain's hypothesised mechanisms for processing sensory information, predicting future states, and selecting actions based on internal world models [104]. The modules proposed by Yann LeCun [104] include:

- Perception Module: Encodes sensory inputs into a joint embedding space.
- World Model Module: Learns the relationships between different sensory modalities and predicts potential future states.
- Actor Module: Interacts with the world.
- Memory Module: Stores and retrieves relevant information from past experiences.
- Cost Module: Evaluates the cost of actions and plans based on the predicted outcomes.
- Configurator Module: Configures the model's parameters and hyper-parameters for specific tasks.

Several recent implementations of JEPA architecture have been proposed, including V-JEPA2 [103], which focuses on video data, and MC-JEPA [109], which extends the architecture to handle multiple modalities such as motion and content data. These models have shown promising results in various tasks, including video prediction, action recognition, and multimodal understanding. However, they only address part of the modular approach proposed by LeCun, focusing instead on the world model and perception modules, for short term task planning. Video game data is already a rich source of training data for deep neural networks, and JEPA's architecture is particularly well-suited for learning from this data due to its ability to process and predict complex relationships between different modalities.

The two main stages required to train a JEPA model: self-supervised pre-training and fine-tuning for downstream tasks. Then we will discuss the data requirements for each stage and how gaming data can be used to train the model effectively in the future of this project.

4.2 Self-Supervised Training

At the heart of the V-JEPA2 architecture is a self-supervised learning stage to build a latent space representation of video frames. This is learnt without labelled data and the reduced dimensionality creates a representation of the video without the need to understand pixel-level information. This paradigm makes JEPA's architecture suitable for learning "*world-model*" representations that understand the dynamics of a video environment via concepts.

The JEPA architecture builds a latent space representation through self-supervised learning without labelled data. Video segments are masked both temporally and spatially using the "multi-block" approach that masks large continuous blocks. The encoders job is to translate the un-masked parts of the video segment into a joint embedding space, such that a predictor can predict the masked segments from the joint embedding (see: **Figure 2** (b)).

Vision Transformers (ViT) serves as both an encoder and predictor, with 3D rotary positional encodings added to understand temporal and spatial relationships. An exponential moving average (EMA) encoder provides training stability and reduces representation collapse between the masked and unmasked segments. The $L1$ loss between predictor and EMA encoder outputs drives the learning process.

As a result this process build a concept based on a latent space representation of the video segments, where each segment is represented by a joint embedding that captures the underlying representation of the video and allows the model to be able to predict future frames based on conceptual rules. This means that world models, like JEPA, are able to understand physical laws from video segments, such as gravity, friction, and momentum, without the need for explicit labels or annotations.

4.3 Fine-Tuning for Downstream Tasks

Once the pre-trained latent space is established, JEPA can be fine-tuned for specific downstream tasks. This involves training task-specific heads on top of the joint embedding space learned during pre-training. The fine-tuning process allows the model to adapt to specific tasks while leveraging the rich representations learned from the video segments (see: **Figure 2** (c)).

A magnitude of tasks can be trained on top of the pre-trained latent space, allowing the model to generalise to new tasks without the need for extensive retraining. This is particularly useful in gaming environments, where the model can learn from player actions, game states, and other relevant information in combination with the joint embedding space to build autonomous agents.

Downstream task-specific models examples:

- **Player Action Prediction**: Predicting next actions based on current game state
- **Game State Classification**: Identifying current context (combat, exploration, crafting)
- **Player Behaviour Analysis**: Analysing patterns and skill levels

The first step in training a downstream task is to freeze the encoder modules from the pre-training phase, maintaining the representations learned from the video segments.

4.3.1 Task-Specific Head

Next, we will add a task-specific head to the model, which will be trained to predict the desired output based on the joint embedding from the JEPA model. For example, for player action prediction, we can use a simple feed-forward neural network that takes the joint embedding as input alongside any player actions performed during the video segment and outputs the next predicted player action.

For game state classification, we can use a multi-class classification head that takes the joint embedding as input and outputs the predicted game state. An example of this is predicting where in the world a player currently is, such as in a city, forest, or dungeon. For player behaviour analysis, we can use a regression head that takes the joint embedding as input and outputs a continuous value representing the player's skill level or play style.

Zero-shot learning can also be applied to the downstream tasks, where the model can predict player actions or game states without any additional training. This is possible due to the rich joint embedding space learned during pre-training, which captures the underlying structure of the data and allows for generalisation to new tasks.

4.4 Data Requirements

The data requirement to train JEPA models vary drastically between the pre-trained stage and the downstream task training stage. V-JEPA was pre-trained with the 2 million videos sourced from public repositories. [110] V-JEPA2 vastly scaled up this pre-training with over 1 million hours of video data collected from the internet. The resulting scale up increased performance of many downstream tasks.[103] It is important to note that the pre-training stage is not limited to video data, but can also include other modalities such as text and audio allowing these modalities to be connected in the latent space. [109, 105] Downstream tasks, however, require far less data to train, creating a opportunity for the industry to make use of these model for specific tasks at much lower development costs.

When pre-training JEPA models, data preparation concepts can be applied to reduce bias and increase sample counts. Geometric augmentation such as cropping, flipping, rotation and colour modification can be applied alongside temporal augmentation such as time stretching, speed changes, and frame skipping. These techniques can be applied to the video segments to increase the diversity of the data and reduce bias in the pre-training stage. In a multimodal setting text and audio can be aligned with video to create a joint representation. An example related to gaming data may use aligned action descriptions or player classification with video segments to balance the pre-training dataset, allowing the joint embedding space to have equal access to edge-cases based on player actions or behaviours.

5. How Can Gaming Data Progress World Model Research

While V-JEPA2 demonstrates significant advances in self-supervised video learning, achieving 77.3% top-1 accuracy on Something-Something v2 and state-of-the-art performance on human action anticipation (39.7 recall-at-5 on Epic-Kitchens-100), it is still in progress research. Furthermore, recent evaluation frameworks like WorldSimBench provide comprehensive dual evaluation approaches for world simulators, encompassing both perceptual and manipulative capabilities [111]. By integrating gaming data into JEPA training pipelines, we can address not just the current limitations the V-JEPA2 team has identified but open future directions of research, critical for advancing toward more capable, generalisable AI systems.

5.1 Multimodal Tasks

While V-JEPA2 currently relies on image goals, with authors acknowledging "*it may be more natural to express goals in other forms, such as with language,*" gaming environments with rich narrative content and text-based objectives provide natural language goal alignment that could bridge this gap.

The V-JEPA2 training approach reveals another critical gap through its reliance on passive observational data from internet videos lacking first-person agency in the pre-training phase. While the downstream objectives developed from the vision-only pre-training phase capture a rich landscape of cause and effect, the lack of action conditioned data availability could limit the models ability to connect actions to world states. V-JEPA2 required an additional post-training with 62 hours of robot interaction data from the Droid dataset to achieve action-conditioned planning capabilities with impressive results. [103] Gaming data naturally provides these missing elements, where every gaming session delivers clear action→consequence relationships, offering vast quantities of data that could dramatically enhance planning capabilities in both pre and post-training without expensive robotic setups.

5.2 Scaling

V-JEPA2 scales their model from 300M to 1B parameters, achieving "*consistent performance improvements while scaling.*" They attribute the ability to scale partly to the 3D-RoPE positional embeddings used helping adjust to longer time horizons. [112] They further argue, the scale of the dataset size used in the pre-training phase is a key factor in the performance improvements. We argue that video gaming's virtually unlimited data generation is an ideal solution to assist in the scaling up of these models.

5.3 Cost Module

The modular vision of the original JEPA proposal by LeCun includes a cost module that evaluates the cost of actions and plans based on the predicted outcomes. This module is critical for enabling the agent to make informed decisions about which actions to take in a given situation. This includes intrinsic costs, sometimes referred to as guard rails or safety constraints, and extrinsic costs, related to achieving a specific goal or task.

For example, take an agent trying to reach a block across a lava pool in Minecraft, the model needs to predict the cost of jumping into the lava, losing health but getting to the goal quickly, or the cost of walking around the lava and finding a safe path. The intrinsic cost for the first plan would be high if the agent is designed to avoid harming itself with a low extrinsic cost. Alternatively, option two offers the reverse cost magnitudes. As intrinsic costs are usually set to be very high as a guard rail, the combination of the costs would result in option two being the most suitable. The world model is used to predict the outcomes of the agent's action sequences.[104]

One potential application of video game data is to test these principles in a controlled environment. In this setup a model would be trained with all possible actions in a video game and then evaluated by being explicitly told to not use a specific action, such as "*swing a sword*" or "*shoot a gun*". The model would then be evaluated on how well it can avoid these actions while still achieving its goals. This is a common evaluation regime in RL agent applications and recent work has shown that cost functions can be learned to reduce or eliminate violations via bi-level optimisation.[113]

5.4 Memory Module

The original JEPA architecture proposed by Yann LeCun suggests a short-term memory module that can store costs and action states to improve long-term planning capabilities and has yet to be implement into SOTA models.[104] Video game environments provide multi-scale memory tasks that humans perform naturally whilst playing games. For example, sub-conscious memorisation of a health bar and its meaning or the conscious memorisation and planning required to solve a difficult puzzle. Future work could explore how to implement a memory module in JEPA that can store and retrieve information about player actions, game states, and long-term objectives. This would allow the model to maintain context over extended gameplay sessions and improve its ability to plan and predict player actions. How to effectively manage the agent's memory and ensure that it can retrieve relevant information when needed is a complex task. The memory module needs to be able to store and retrieve information about previous tasks, sub-tasks, and player actions in a way that is efficient and effective. Common Large Language Models (LLMs) use techniques such as vector databases and knowledge graphs can be used to store and retrieve information with RAG (Retrieval Augmented Generation) techniques.[114, 115, 116] However, in dynamic environments such as video games, the memory module needs to be able to adapt to changes in the game environment and data modalities, whilst updating knowledge accordingly.

5.5 Hierarchical Planning

The authors of [103] explicitly identify hierarchical planning as a critical gap, stating the need for "*developing approaches for hierarchical models capable of making predictions across multiple spatial and temporal scales, at different levels of abstraction.*" As a result they limit their planning evaluations to 16s "*pick-and-place*" manipulation tasks without sub-goals. LeCun has proposed that JEPA models will address this issue with hierarchical planning, combining short and long term objectives. Current video game quest systems and difficulty progression naturally decompose complex objectives into hierarchical sub-tasks, from tactical combat decisions (seconds) to resource management (minutes) to campaign strategy (hours), providing exactly the multi-scale structure needed for hierarchical world model development. Strategy games like StarCraft II, through AlphaStar and other RL algorithms, have already demonstrated models for planning horizons extending to thousands of timestamps, and integration of the two approaches could lead to even more capable models.[4, 117] The well defined, bounded framework that video game data provides is a key step to solve hierarchical planning problems before moving to real-world fuzzy goals. Additionally research has already validated this approach in world models through Microsoft's World and Human Action Model (WHAM), which demonstrates 85%+ persistence rates for user modifications through generated sequences when trained on gaming data [118], showing how such data enables consistent long-term planning capabilities that address JEPA's future development.

5.6 Multi-Agent Coordination

Due to the wide variety of game genres that include many types of multi-player interactions, gaming data is a rich source for training multi-agent coordination models. This includes cooperative tasks (e.g., team-based objectives), competitive scenarios (e.g., player-versus-player), and complex social interactions (e.g., guilds, clans). Embedding these interactions into the joint embedding space is key, if AI agents using the JEPA architecture are to work well as a team. It is still unclear as to what form training these types of behaviours would take. Future work should focus on how to effectively implement these multi-agent dynamics into the embedding space and if these behaviours can be learnt from examples.

5.7 Data Curriculums, Diversity & Transfer Learning

V-JEPA2 uses a dynamically scaling curriculum to scale the pre-training stage, allowing for higher resolution and longer segments of videos. [103] We suggest using player metrics to create a curricula for learning complex tasks, starting with tasks that took a short time to complete with high success rates, to more complex longer tasks with deeper planning and more complex action sequences. RL curricula are a common part of learning structures and applying these to self-supervised learning could increase the efficiency of the pre-training stage.

The V-JEPA2 paper emphasises the importance of diverse training scenarios, yet internet videos provide limited coverage of edge cases. Gaming's procedural generation creates unlimited scenario variations that stress-test model capabilities—games like No Man's Sky generate 18 quintillion unique planets, providing the comprehensive coverage needed to develop robust world models capable of handling novel situations.

While JEPA models have shown success when trained with real-world datasets, their adoption of video game data is still in its infancy. Future research should investigate bidirectional transfer learning between real-world and gaming datasets, examining how pre-trained models from each domain adapt to the other's unique characteristics. This includes systematic comparison of learned latent spaces from gaming versus real-world pre-training, potentially revealing domain-specific patterns that could enhance both environments.

5.8 Real-Time Decision Making

Current JEPA implementations analyse fixed-length video segments (e.g., 3 to 16 seconds). However, streaming data from video game environments could enable continuous prediction of player actions over time. This would allow for real-time classification or prediction of player actions, enhancing the model's applicability in dynamic gaming scenarios and link the JEPA architecture to biological systems that process continuous streams of data. Other architectures, such as GENIE 3 [28] and Matrix Game [119], have shown impressive real-time performance, that JEPA would need to match to be applicable in real-time scenarios.

5.9 Tool Use

JEPA's current architecture does not explicitly model tool use, which is a critical aspect of human decision-making in complex environments. Many LLM based agents have shown impressive tool use capabilities with chain-of-thought loops and tool use [120]. Tool use can require either system 1 or system 2 level thinking, depending on the complexity of the overall task or the tool itself. Gaming data is a rich source of these types of interactions and therefore, positions itself as a key training resource for agentic training.

5.10 Interpretability

JEPA models are inherently different to generative models such as LLMs, because of which they come with different challenges for Interpretability and trust. The latent space representation of JEPA captures the relationships between different modalities making interpretation difficult. In comparison a generative LLM that uses chain-of-thought tracing may be easier to understand the reasons why a specific action was taken.

5.11 Emergent Behaviours

Gaming data's procedural generation and emergent gameplay patterns offer opportunities to discover unexpected AI capabilities. Future research should systematically explore how models trained on gaming data develop emergent skills that transfer to unforeseen applications, potentially revealing new paradigms for general intelligence development.

5.12 Future Directions

The integration of JEPA architectures with gaming data opens unprecedented opportunities for AI development, with implications extending far beyond current implementations. The efficiency gains demonstrated by V-JEPA-AC—requiring only 62 hours of robot arm video and action data for downstream tasks compared to 1.6 million hours for pre-training [103]—highlight the transformative potential of this approach. This efficiency stems from JEPA's rich joint embedding space that captures underlying data structure, enabling both efficient downstream training and zero-shot learning capabilities where models can predict player actions or game states without additional training.

These research directions collectively position gaming data and JEPA integration as a cornerstone for next-generation AI development, offering pathways to more efficient training, improved generalisation, and enhanced real-world applicability. The unique characteristics of gaming environments—their natural supervision signals, temporal richness, and multimodal alignment—create ideal conditions for advancing fundamental AI capabilities while maintaining practical applicability of agents across diverse domains.

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