Novelty Assessment Report

Paper: Mean-Field Neural Differential Equations: A Game-Theoretic Approach to Sequence Prediction
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Abstract

We propose a novel class of neural differential equation models called mean-field continuous sequence predictors (MFPs) for efficiently generating continuous sequences with potentially infinite-order complexity. To address complex inductive biases in time-series data, we employ mean-field dynamics structured through carefully designed graphons. By reframing continuous sequence prediction as mean-field games, we utilize a fictitious play strategy integrated with gradient-descent techniques. This approach exploits the stochastic maximum principle to determine the Nash equilibrium of the system. Both empirical evidence and theoretical analysis highlight the unique advantages of our framework, where a collective of continuous predictors achieves highly accurate predictions and consistently outperforms benchmark prior works.

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Core Task Landscape

This paper addresses: **continuous sequence prediction with neural differential equations**
A total of **50 papers** were analyzed and organized into a taxonomy with **26 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:
- **Core Neural Differential Equation Architectures and Theoretical Foundations**
- **Attention Mechanisms and Hybrid Architectures for Continuous-Time Modeling**
- **Irregular and Incomplete Time Series Modeling**
- **Spatiotemporal and Graph-Structured Dynamics**
- **Domain-Specific Forecasting Applications**
- **Specialized Prediction Tasks and Data Modalities**
- **Advanced Architectures and Methodological Innovations**
- **Comprehensive Reviews and Surveys**

Complete Taxonomy Tree

- continuous sequence prediction with neural differential equations Survey Taxonomy
- Core Neural Differential Equation Architectures and Theoretical Foundations
  - Foundational Neural ODE and NDE Theory (2 papers)
  - [1] On neural differential equations (Kidger, 2022) View paper
  - [24] Neural ordinary differential equations (Chen, 2018) View paper
  - Stochastic and Jump Process Extensions (3 papers)
  - [6] Neural jump stochastic differential equations (Junteng Jia, 2019) View paper
  - [38] Stable Neural Stochastic Differential Equations in Analyzing Irregular Time Series Data (Oh, 2024) View paper
  - [49] Neural SDEs as a Unified Approach to Continuous-Domain Sequence Modeling (Shen Macheng, 2025) View paper
  - Neural Controlled Differential Equations (3 papers)
  - [11] Learnable path in neural controlled differential equations (Jhin, 2023) View paper
  - [19] Continuous-Time SO(3) Forecasting with Savitzky--Golay Neural Controlled Differential Equations (Bastian, 2025) View paper
  - [23] Exit: Extrapolation and interpolation-based neural controlled differential equations for time-series classification and forecasting (Sheo Yon Jhin, 2022) View paper
  - Stability and Long-Horizon Dynamics (2 papers)
  - [7] Hierarchical deep learning of multiscale differential equation time-steppers (Yuying Liu, 2022) View paper
  - [13] Stabilized neural ordinary differential equations for long-time forecasting of dynamical systems (Alec J. Linot, 2023) View paper
- Attention Mechanisms and Hybrid Architectures for Continuous-Time Modeling
  - Continuous-Time Attention in Neural Differential Equations (2 papers)
  - [3] Continuous-time self-attention in neural differential equation (Jenâ￼￼Tzung Chien, 2021) View paper
  - [31] Continuous-time attention for sequential learning (Jenâ￼￼Tzung Chien, 2021) View paper
  - Transformer-Based Continuous-Time Models (2 papers)
  - [25] Integrating Ordinary Differential Equations with Sparse Attention for Power Load Forecasting (Jiacheng Li, 2025) View paper
  - [37] Contiformer: Continuous-time transformer for irregular time series modeling (Chen Yuqi, 2023) View paper
  - Hybrid Discrete-Continuous Coordination (2 papers)
  - [18] Neural predictive control to coordinate discrete-and continuous-time models for time-series analysis with control-theoretical improvements (Li, 2025) View paper
  - [27] Continuous Depth Recurrent Neural Differential Equations (Anumasa Srinivas, 2023) View paper

- Comprehensive Reviews and Surveys (1 papers)
  - [4] Comprehensive review of neural differential equations for time series analysis (Oh, 2025) View paper

Narrative

Core task: continuous sequence prediction with neural differential equations. The field has matured into a rich ecosystem organized around several complementary themes. At the foundation lie core architectures and theoretical underpinnings—works such as Neural Ordinary Differential Equations[24] and Neural Differential Equations[1] establish the basic continuous-time modeling paradigm. From this base, the taxonomy branches into attention-based and hybrid designs (e.g., Self-Attention NDE[3], Contiformer[37]) that blend discrete attention with continuous dynamics, methods tailored for irregular or incomplete observations (Latent ODE Irregular[50], Neural Jump SDE[6]), and spatiotemporal or graph-structured extensions (Graph ODE Survey[10], Adaptive Graph NODE Traffic[20]) that capture relational dependencies. Parallel branches address domain-specific forecasting (Wind Power NCDE[12], Suicide Risk NODE[2]), specialized prediction tasks across diverse data modalities (NODER Image Regression[30], SO3 Forecasting NCDE[19]), and advanced methodological innovations including stabilization techniques (Stabilized NODE Forecasting[13]) and cross-domain transfer (Cross-Domain NSDE[5]). Comprehensive reviews (NDE Time Series Review[4]) synthesize these directions, highlighting both the breadth of applications and the ongoing theoretical challenges.

Within the advanced methodological branch, a small but growing cluster explores mean-field and game-theoretic formulations that recast sequence prediction as a collective optimization or equilibrium problem. Mean-Field Game Sequence[0] exemplifies this direction, framing continuous dynamics through the lens of interacting agents whose aggregate behavior emerges from strategic interactions. This contrasts with more conventional architectures like Self-Attention NDE[3], which augment standard NODE frameworks with attention layers but retain a single-agent perspective, and Cross-Domain NSDE[5], which emphasizes stochastic regularization and domain adaptation rather than game-theoretic equilibria. By situating sequential prediction in a mean-field game setting, Mean-Field Game Sequence[0] opens new avenues for modeling competitive or cooperative dynamics in time series, distinguishing itself from neighboring works that focus on architectural hybridization or robustness to distribution shift.

Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

Taxonomy-Level Summary

The original leaf focuses on mean-field and game-theoretic formulations that model collective dynamics and multi-agent interactions for neural differential equations in sequence prediction. The sibling subtopics represent orthogonal methodological concerns: Bayesian training addresses probabilistic inference methods, Explainability focuses on interpretability and transparency, Meta-Learning examines continuous learning rules and adaptive systems, while Tensorized approaches handle high-dimensional structured data. These siblings emphasize different aspects of neural ODE methodology rather than the multi-agent collective dynamics perspective.

Similarities: - All subtopics work within the neural differential equations framework for continuous-time sequence modeling - Each addresses specific methodological challenges in training, interpreting, or structuring neural ODEs - All aim to extend basic neural ODE capabilities beyond standard single-agent deterministic formulations

Differences: - Original leaf uniquely focuses on multi-agent and collective dynamics using game theory and mean-field approximations, while siblings address single-model concerns - Bayesian/Probabilistic Training emphasizes uncertainty quantification and efficient fitting through probabilistic methods, not multi-agent interactions - Explainability prioritizes interpretability and transparency of learned dynamics, orthogonal to the game-theoretic modeling perspective - Meta-Learning focuses on learning-to-learn and adaptive rule discovery, distinct from equilibrium-based collective behavior - Tensorized approaches address computational structure for high-dimensional data representation, not agent-based formulations

Suggested Search Directions: - Multi-agent reinforcement learning with continuous-time dynamics and mean-field games - Population-based training methods for neural differential equations - Collective behavior modeling and swarm intelligence using differential equations - Nash equilibrium computation in continuous-time neural systems

Sibling Subtopics

- **Bayesian and Probabilistic Training** (leaves: 1, papers: 1)
- Scope: Bayesian inference methods for neural differential equations including gradient matching and probabilistic regularization for efficient fitting.
- Exclude: Deterministic training methods and non-Bayesian approaches belong to other categories.
- **Explainability and Interpretable Dynamics** (leaves: 1, papers: 1)
- Scope: Methods enhancing interpretability of neural differential equations through attention visualization, expert knowledge integration, and explainable temporal patterns.
- Exclude: Black-box methods and non-interpretable architectures belong to other categories.
- **Meta-Learning and Continuous Learning Rules** (leaves: 1, papers: 1)
- Scope: Neural differential equations for learning continuous-time learning rules and meta-learning frameworks that program neural networks through ODEs.
- Exclude: Standard supervised learning and discrete update rules belong to other categories.
- **Tensorized and High-Dimensional Representations** (leaves: 1, papers: 1)
- Scope: Tensor-based neural ODE architectures for handling high-dimensional multivariate data with structured decompositions and arbitrary-step prediction.
- Exclude: Standard vector-based representations and low-dimensional methods belong to other categories.

Contributions Analysis

Overall novelty summary. The paper introduces mean-field continuous sequence predictors (MFPs) that frame continuous sequence prediction as mean-field games, employing fictitious play and gradient-descent techniques to find Nash equilibria. According to the taxonomy, this work occupies the 'Mean-Field and Game-Theoretic Formulations' leaf under 'Advanced Architectures and Methodological Innovations'. Notably, this leaf contains only the original paper itself—no sibling papers are present—indicating this is a sparse, emerging research direction within the broader neural differential equation landscape of fifty papers across twenty-six leaf nodes.

The taxonomy reveals that neighboring leaves focus on distinct methodological innovations: 'Tensorized and High-Dimensional Representations' addresses structured decompositions for multivariate data, 'Bayesian and Probabilistic Training' emphasizes gradient matching and probabilistic regularization, and 'Meta-Learning and Continuous Learning Rules' explores learning-to-learn frameworks. The scope note for the original paper's leaf explicitly excludes 'single-agent formulations and standard neural ODE training', positioning game-theoretic collective dynamics as a departure from conventional attention-based hybrids (e.g., Self-Attention NDE) and stochastic extensions (e.g., Cross-Domain NSDE) found in other branches.

Among thirty candidates examined, the contribution-level analysis shows mixed novelty signals. The core MFP framework (Contribution A) examined ten candidates with one refutable match, suggesting some prior work on mean-field neural models exists within the limited search scope. The game-theoretic formulation (Contribution B) found no refutable candidates among ten examined, indicating this

framing appears less explored. The gradient-based FBSDE approach for Nash equilibria (Contribution C) also identified one refutable candidate among ten, pointing to existing work on equilibrium computation methods. These statistics reflect a top-K semantic search, not exhaustive coverage.

Given the limited search scope and the paper's placement in an otherwise-empty taxonomy leaf, the work appears to explore a relatively novel intersection of mean-field theory and neural differential equations for sequence prediction. However, the presence of refutable candidates for two of three contributions suggests that individual technical components may have precedents. The analysis cannot rule out additional relevant work beyond the thirty candidates examined, particularly in adjacent game theory or mean-field control literature not captured by semantic search.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Mean-field continuous sequence predictors (MFPs) for continuous sequence modeling

Description: The authors introduce a new neural differential equation framework that models continuous sequences using mean-field dynamics structured through neural graphons. This approach addresses complex inductive biases in time-series data by representing a continuum of predictors that collectively generate accurate forecasts.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Neural stochastic differential games for time-series analysis
URL: View paper

Prior Art Analysis

Neural Stochastic Games[63] demonstrates that prior work exists on using neural differential equations with game-theoretic frameworks for time-series analysis. Both papers employ stochastic differential equations controlled by neural agents to model temporal dynamics, utilize game-theoretic principles (differential games vs. mean-field games) to coordinate multiple predictors/agents, and aggregate individual predictions through weighted mechanisms. The candidate paper was published in ICML 2023, predating the original submission to ICLR 2026, and presents a multi-agent neural SDE framework with cooperative differential games that shares fundamental architectural and methodological similarities with the original paper's mean-field approach.

Evidence

Evidence 1 - **Rationale**: Both papers propose neural differential equation frameworks for time-series analysis that employ game-theoretic principles to coordinate multiple predictors/agents, demonstrating that the concept of using game theory with neural differential equations for sequence modeling existed prior to the original paper. - **Original**: we propose a novel class of neural differential equation models calledmeanfield continuous sequence predictors(mfps) for efficiently generating continuous sequences with potentially infinite-order complexity. to address complex inductive biases in time-series data, we employ mean-field dynamics stru... - **Candidate**: modeling spatiotemporal dynamics with neural differential equations has become a major line of research that opens new ways to handle various real-world scenarios (e.g., missing observations, irregular times, etc.). despite such progress, most existing methods still face challenges in providing a ge...

Evidence 2 - **Rationale**: Both papers employ game-theoretic frameworks with multiple interacting agents seeking Nash equilibrium for time-series prediction, showing that the game-theoretic approach to continuous sequence modeling was established in prior work. - **Original**: the mean-field principle, a core philosophy in various scientific domains including neuroscience (faugeras et al., 2009), statistical physics (negele, 1982), and economics (carmona, 2020; cardaliaguet & lehalle, 2018), serves as a powerful tool to model and analyze a large number of interacting agen... - **Candidate**: to address the above requirements, we propose a novel framework to formalize the time-series prediction problem as a cooperative differential games between multiple agents. cooperative differential games have been extensively studied in many disciplines (perelman et al., 2011; jørgensen et al., 2010...

Evidence 3 - **Rationale**: Both papers aggregate individual predictor/agent decisions through weighted mechanisms to produce final predictions, showing that the architectural pattern of aggregating multiple neural-controlled trajectories for sequence prediction was established in prior work. - **Original**: the overarching goal is then to calibrate the trajectory of predictors by determining the optimal neural agent $\alpha*$ that closely approximates the target future interval, e.g.,e t[‖eu∞xα∗ u∞(t)-y t‖2 e]≈0 , where decision aggregation w:o→[0,1] captures the collective behavior of mean-field predictors. - **Candidate**: definition 2.2. (multi-conditioned predictor)2 let us define a simplex-valued function aα t : t x rd x θ → ∆i. then, the prediction made by proposed masdes is defined as follows: dλα t := x i∈n aαi t bαi t - 1 2 ∇ ·σt + σt∇log pi t(·|ysi) dt , where we denote σtσt t := σt

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2. Deeper Learning: Residual Networks, Neural Differential Equations and Transformers, in Theory and Action
URL: View paper

Brief Assessment

Deeper Learning Theory[68] focuses on residual networks and neural ODEs for general deep learning architectures, not on mean-field game formulations for continuous sequence prediction with graphon structures.

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3. Neural graphical modelling in continuous-time: consistency guarantees and algorithms
URL: View paper

Brief Assessment

Neural Graphical Continuous-Time[64] focuses on structure learning and causal discovery in dynamical systems using neural ODEs, not on mean-field game-theoretic frameworks for sequence prediction with graphon-structured interactions.

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4. Efficient inference on a network of spiking neurons using deep learning
URL: View paper

Brief Assessment

Spiking Networks Deep Learning[62] focuses on inference on mean-field models of spiking neurons for neural computation, not continuous sequence prediction or time-series forecasting. The application domains and technical objectives are fundamentally different.

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5. Continuous limits of residual neural networks in case of large input data
URL: View paper

Brief Assessment

Continuous Limits ResNets[66] focuses on mean-field limits of residual neural networks for large input data in supervised learning contexts, not on continuous sequence prediction with mean-field dynamics for time-series forecasting.

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6. Stochastic mean-field formulation of the dynamics of diluted neural networks
URL: View paper

Brief Assessment

Stochastic Mean-Field Dynamics[70] focuses on pulse-coupled neural networks with synaptic dilution for neuroscience modeling, not continuous sequence prediction or time-series forecasting with neural differential equations.

7. Simulation-Free Differential Dynamics through Neural Conservation Laws
URL: View paper

Brief Assessment

Neural Conservation Laws[67] focuses on simulation-free training of diffusion processes using neural conservation laws and likelihood-based models for general objective functions, not on mean-field game-theoretic sequence prediction frameworks with graphon structures.

8. Improving neural ordinary differential equations with Nesterov's accelerated gradient method
URL: View paper

Brief Assessment

Nesterov Accelerated NODE[65] focuses on improving neural ODEs using Nesterov's accelerated gradient method for general dynamical systems, not on mean-field dynamics or game-theoretic sequence prediction frameworks.

9. Graph Neural Differential Equations for Coarse-Grained Socioeconomic Dynamics
URL: View paper

Brief Assessment

Graph NDE Socioeconomic[69] focuses on coarse-grained socioeconomic dynamics using graph neural differential equations, not continuous sequence prediction with mean-field game frameworks for time-series forecasting.

10. Controllability of continuous networks and a kernel-based learning approximation
URL: View paper

Brief Assessment

Controllability Continuous Networks[61] focuses on controllability theory and training of residual neural networks through mean-field equations, not on continuous sequence prediction tasks for time-series data.

Contribution 2: Game-theoretic formulation of continuous sequence prediction as mean-field games

Description: The authors reframe the continuous sequence prediction task as a mean-field game where infinitely many agents (predictors) interact to satisfy Nash equilibrium. This game-theoretic interpretation enables systematic modeling of continuous-time sequences with increasingly fine temporal granularity.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Toward Practical Forecasts of Public Sentiments via Convexification for Mean Field Games: Evidence from Real World COVID-19 Discussion Data
URL: View paper

Brief Assessment

Sentiment Forecasting MFG[55] applies mean-field games to sentiment forecasting with convexification methods, not to general continuous sequence prediction tasks. The candidate focuses on forecasting public sentiment dynamics from social media data, while the original paper addresses continuous-time sequence prediction across diverse domains using neural differential equations.

2. Graphon Mean Field Games with Finite States and Forecasting Models for the Energy Market
URL: View paper

Brief Assessment

Graphon Mean Field Games[57] focuses on finite-state graphon mean field games with applications to energy markets, not continuous sequence prediction. The candidate addresses equilibrium existence and uniqueness in discrete state spaces with heterogeneous interactions via graphons, whereas the original paper models continuous-time sequences with infinite-order complexity using mean-field dynamics for prediction tasks.

3. Mean-field Continuous Sequence Predictors
URL: View paper

Brief Assessment

Mean-Field Sequence Predictors[60] presents nearly identical content to the original paper, including the same game-theoretic formulation, mean-field graphon SDEs, and Nash equilibrium approach. This appears to be the same work or a closely related version rather than independent prior work that could refute novelty claims.

4. Unified continuous-time q-learning for mean-field game and mean-field control problems
URL: View paper

Brief Assessment

Unified Q-Learning MFG[59] focuses on continuous-time Q-learning for mean-field game and control problems in jump-diffusion models, not on continuous sequence prediction or forecasting tasks.

5. Learning in Mean-Field Games and Continuous-Time Stochastic Control Problems
URL: View paper

Brief Assessment

Learning Mean-Field Games[54] focuses on reinforcement learning algorithms for large population games and continuous-time stochastic control problems, not on continuous sequence prediction or time-series forecasting tasks.

6. A case for mean field games in airspace congestion forecasting
URL: View paper

Brief Assessment

Airspace Congestion MFG[52] applies mean field games to airspace congestion forecasting, not continuous sequence prediction. The candidate focuses on aircraft behavior patterns in airspace operations, while the original paper addresses general continuous-time sequence modeling across diverse domains (robotics, medical time series, air quality).

7. Forecasting Public Sentiments via Mean Field Games
URL: View paper

Brief Assessment

Public Sentiments MFG[56] focuses on forecasting public sentiments using mean-field games for PDEs with opposite time directions, not on continuous sequence prediction with neural differential equations. The candidate addresses a fundamentally different problem domain (social phenomena forecasting) with different mathematical structures (coupled nonlinear parabolic PDEs) compared to the original's neural ODE/SDE framework for time-series prediction.

8. Mean Field Guided Machine Learning
URL: View paper

Brief Assessment

Mean Field Guided ML[53] appears to be a book exploring mean field games in general contexts. The provided excerpt is too brief and lacks specific technical details about continuous sequence prediction formulations to assess whether it challenges the original paper's novelty claim.

9. Multi-agent reinforcement learning: A mean-field perspective
URL: View paper

Brief Assessment

Multi-Agent Mean-Field[58] focuses on multi-agent reinforcement learning for competitive and cooperative control problems in discrete decision-making contexts, not continuous sequence prediction or time-series forecasting tasks.

10. Actor-critic reinforcement learning algorithms for mean field games in continuous time, state and action spaces
URL: View paper

Brief Assessment

Actor-Critic Mean Field[51] focuses on developing actor-critic reinforcement learning algorithms for mean field games in continuous spaces, not on formulating sequence prediction tasks as mean-field games. The candidate addresses algorithmic solutions for existing MFG problems rather than proposing a novel game-theoretic interpretation of continuous sequence prediction.

Contribution 3: Gradient-based mean-field FBSDE approach for approximating Nash equilibria

Description: The authors develop a computational method based on forward-backward stochastic differential equations (FBSDEs) integrated with gradient descent techniques. This approach exploits the stochastic maximum principle to determine Nash equilibrium and provides theoretical guarantees on convergence and sample complexity.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Stochastic graphon mean field games with jumps and approximate nash equilibria
URL: View paper

Brief Assessment

Stochastic Graphon MFG[76] focuses on graphon mean field games with heterogeneous interactions and jumps, not on general gradient-based FBSDE methods for Nash equilibria approximation in continuous sequence prediction tasks.

2. Mean-field type forward-backward doubly stochastic differential equations and related stochastic differential games
URL: View paper

Prior Art Analysis

Mean-Field Forward-Backward SDE[72] demonstrates that the use of forward-backward stochastic differential equations (FBSDEs) integrated with the stochastic maximum principle to determine Nash equilibria in mean-field games predates the original paper's contribution. Both papers employ fully coupled mean-field FBSDEs and utilize the stochastic maximum principle to characterize Nash equilibrium points. The candidate paper explicitly addresses 'fully coupled mean-field forward-backward stochastic differential equations and stochastic maximum principle' for obtaining 'unique nash equilibrium point,' which directly overlaps with the original paper's claimed novel approach of using 'forward-backward stochastic differential equations (FBSDEs) integrated with gradient descent techniques' that 'exploits the stochastic maximum principle to determine Nash equilibrium.'

Evidence

Evidence 1 - **Rationale**: Both papers explicitly use mean-field FBSDEs to approximate/obtain Nash equilibria in mean-field games, demonstrating that this approach was already established in the candidate paper. - **Original**: we propose a gradient-based mean-field fbsde approach that provides feasible computational complexity for approximating nash equilibria in mean-field games - **Candidate**: in order to obtain the unique nash equilibrium point, we study a new kind of fully coupled mean-field forward-backward stochastic differential equations and stochastic maximum

Evidence 2 - **Rationale**: The candidate paper explicitly mentions using the stochastic maximum principle in conjunction with mean-field FBSDEs to obtain Nash equilibrium, which is the same methodological approach claimed as novel in the original paper. - **Original**: this approach exploits the stochastic maximum principle to determine the nash equilibrium of the system - **Candidate**: in order to obtain the unique nash equilibrium point, we study a new kind of fully coupled mean-field forward-backward stochastic differential equations and stochastic maximum

Evidence 3 - **Rationale**: Both papers formulate gradient systems based on forward-backward stochastic differential equations for mean-field games, indicating that the candidate paper already established this framework for Nash equilibrium computation. - **Original**: definition 3.4.(gradient system of fbsdes) a. for the fixed flow of measures $\nu u(\cdot) : t \to p2$ and the fixed label u at each stage m, we consider a family of processes$(xu(t), y\, u(t), z\, u(t))$ that solves forward-backward stochastic differential equations - **Candidate**: in order to obtain the unique nash equilibrium point, we study a new kind of fully coupled mean-field forward-backward stochastic differential equations and stochastic maximum

3. Markovian-switching systems: Backward and forward-backward stochastic differential equations, mean-field interactions, and nonzero-sum differential games
URL: View paper

Brief Assessment

Markovian-Switching Systems[71] focuses on backward and forward-backward stochastic differential equations with Markovian switching and mean-field interactions in the context of nonzero-sum differential games. The original paper addresses continuous

sequence prediction using mean-field games with gradient descent techniques, which is a different application domain and problem formulation.

4. Mean field games of controls: on the convergence of Nash equilibria
URL: View paper

Brief Assessment

[Final Audit Failure] The model insisted on a refutation claim but failed to provide verifiable evidence after multiple retries. Marked as cannot_refute for safety. Please manually verify the candidate text.

5. Ïµ-Nash mean-field games for stochastic linear-quadratic systems with delay and applications.
URL: View paper

Brief Assessment

Nash Mean-Field Delay[78] focuses on ε-Nash equilibria in mean-field games with delay for linear-quadratic systems, not on gradient-based FBSDE methods for general continuous sequence prediction as in the original paper.

6. Direct Approach of Indefinite Linear-Quadratic Mean Field Games
URL: View paper

Brief Assessment

Indefinite Linear-Quadratic MFG[75] focuses on linear-quadratic mean field games with indefinite control weights using a direct approach via Riccati equations, not gradient descent techniques. The candidate explicitly states they 'use the direct approach to tackle this problem' rather than gradient-based FBSDE methods for Nash equilibrium approximation.

7. On optimal control of coupled mean-field forward-backward stochastic equations
URL: View paper

Brief Assessment

Coupled Mean-Field Control[79] focuses on optimal control of mean-field FBSDEs with relaxed (measure-valued) controls and existence proofs, not on gradient-based computational methods or Nash equilibrium approximation in mean-field games.

8. A mean-field game for a forward-backward stochastic system with partial observation and common noise
URL: View paper

Brief Assessment

Partial Observation MFG[73] focuses on linear-quadratic mean-field games with partial observation and common noise, using filter and dimensional-expansion techniques. The original paper addresses continuous sequence prediction with neural differential equations and general nonlinear dynamics, representing fundamentally different problem domains and methodological approaches.

9. An introduction to mean field game theory
URL: View paper

Brief Assessment

Mean Field Game Introduction[80] is a pedagogical introduction to mean field game theory focusing on PDE approaches and the master equation. It does not present a novel computational gradient-based FBSDE method for approximating Nash equilibria, but rather surveys existing theoretical frameworks.

10. A constraint-preserving neural network approach for mean-field games equilibria
URL: View paper

Brief Assessment

Constraint-Preserving MFG[74] focuses on constraint-preserving neural network methods for MFG equilibria, while the original paper develops a gradient descent-based FBSDE approach specifically for continuous sequence prediction tasks. The candidate's emphasis on constraint preservation represents a different technical focus.

Appendix: Text Similarity Detection

Textual similarity detection checked 30 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Mean-field Continuous Sequence Predictors

Detected in: Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] Mean-Field Neural Differential Equations: A Game-Theoretic Approach to Sequence Prediction View paper
- [1] On neural differential equations View paper
- [2] Continuous time and dynamic suicide attempt risk prediction with neural ordinary differential equations View paper
- [3] Continuous-time self-attention in neural differential equation View paper
- [4] Comprehensive review of neural differential equations for time series analysis View paper
- [5] Improving transferability for cross-domain trajectory prediction via neural stochastic differential equation View paper
- [6] Neural jump stochastic differential equations View paper
- [7] Hierarchical deep learning of multiscale differential equation time-steppers View paper
- [8] Continuous pde dynamics forecasting with implicit neural representations View paper
- [9] Adding attention to the neural ordinary differential equation for spatio-temporal prediction View paper
- [10] Graph odes and beyond: A comprehensive survey on integrating differential equations with graph neural networks View paper
- [11] Learnable path in neural controlled differential equations View paper
- [12] Ultra-short-term Wind power prediction algorithm based on bidirectional neural controlled differential equations View paper
- [13] Stabilized neural ordinary differential equations for long-time forecasting of dynamical systems View paper
- [14] Signed graph neural ordinary differential equation for modeling continuous-time dynamics View paper

- [15] Cotode: Continuous trajectory neural ordinary differential equations for modelling event sequences View paper
- [16] Conditional neural ODE processes for individual disease progression forecasting: a case study on COVID-19 View paper
- [17] Link prediction by continuous spatiotemporal representation via neural differential equations View paper
- [18] Neural predictive control to coordinate discrete-and continuous-time models for time-series analysis with control-theoretical improvements View paper
- [19] Continuous-Time SO(3) Forecasting with Savitzky--Golay Neural Controlled Differential Equations View paper
- [20] Adaptive Correlation Graph Neural Ordinary Differential Equation for Traffic Flow Forecasting. View paper
- [21] ExpertODE: Continuous Diagnosis Prediction with Expert Enhanced Neural Ordinary Differential Equations View paper
- [22] Forecasting with an N-dimensional Langevin equation and a neural-ordinary differential equation View paper
- [23] Exit: Extrapolation and interpolation-based neural controlled differential equations for time-series classification and forecasting View paper
- [24] Neural ordinary differential equations View paper
- [25] Integrating Ordinary Differential Equations with Sparse Attention for Power Load Forecasting View paper
- [26] Monotonic neural ordinary differential equation: Time-series forecasting for cumulative data View paper
- [27] Continuous Depth Recurrent Neural Differential Equations View paper
- [28] Dynamic Personalized Graph Neural Ordinary Differential Equation Network for Multivariate Time Series Prediction of Chemical Processes View paper
- [29] Explainable tensorized neural ordinary differential equations for arbitrary-step time series prediction View paper
- [30] NODER: Image Sequence Regression Based on Neural Ordinary Differential Equations View paper
- [31] Continuous-time attention for sequential learning View paper
- [32] Time-aware neural ordinary differential equations for incomplete time series modeling View paper
- [33] Neural Chronos ODE: Unveiling Temporal Patterns and Forecasting Future and Past Trends in Time Series Data View paper
- [34] Social ode: Multi-agent trajectory forecasting with neural ordinary differential equations View paper
- [35] Transcriptomic forecasting with neural ordinary differential equations View paper
- [36] A framework based on physics-informed graph neural ODE: for continuous spatial-temporal pandemic prediction View paper
- [37] Contiformer: Continuous-time transformer for irregular time series modeling View paper
- [38] Stable Neural Stochastic Differential Equations in Analyzing Irregular Time Series Data View paper
- [39] Continuous-time air pollutant forecasting using multi-timescale attention neural ordinary differential equations (MA-NODE) View paper
- [40] Conditional neural ode for longitudinal parkinson's disease progression forecasting View paper
- [41] Continuous-Time Channel Prediction Based on Tensor Neural Ordinary Differential Equation View paper
- [42] Neural jump ordinary differential equations: Consistent continuous-time prediction and filtering View paper
- [43] Neural differential equations for learning to program neural nets through continuous learning rules View paper
- [44] Neural ordinary differential equation for irregular human motion prediction View paper
- [45] Fast fitting of neural ordinary differential equations by Bayesian neural gradient matching to infer ecological interactions from time‐series data View paper
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