Novelty Assessment Report

Paper: Learning linear state-space models with sparse system matrices
PDF URL: https://openreview.net/pdf?id=0lct7PrPgS
Venue: ICLR 2026 Conference Submission
Year: 2026
Report Generated: 2026-01-05

Abstract

Due to tractable analysis and control, linear state-space models (LSSMs) provide a fundamental mathematical tool for time-series data modeling in various disciplines. In particular, many LSSMs have sparse system matrices because interactions among variables are limited or only a few significant relationships exist. However, current learning algorithms for LSSMs lack the ability to learn system matrices with the sparsity constraint due to the similarity transformation. To address this issue, we impose sparsity-promoting priors on system matrices to balance modeling error and model complexity. By taking hidden states of LSSMs as latent variables, we then explore the expectation-maximization (EM) algorithm to derive a maximum a posteriori (MAP) estimate of both hidden states and system matrices from noisy observations. Based on the Global Convergence Theorem, we further demonstrate that the proposed learning algorithm yields a sequence converging to a local maximum or saddle point of the joint posterior distribution. Finally, experimental results on simulation and real-world problems illustrate that the proposed algorithm can preserve the inherent topological structure among variables and significantly improve prediction accuracy over classical learning algorithms.

Core Task Landscape

This paper addresses: **Learning Linear State-Space Models with Sparse System Matrices**

A total of **50 papers** were analyzed and organized into a taxonomy with **16 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Sparse Parameter Estimation and System Identification**
- **State and Input Estimation with Sparsity Constraints**
- **Sparse Graphical and Structured State-Space Models**
- **Data-Driven Discovery and Nonlinear System Identification**
- **State Space Models with Neural and Deep Learning Components**
- **Applications of Sparse State-Space Models**
- **Theoretical Foundations and General Frameworks**

Complete Taxonomy Tree

- Learning Linear State-Space Models with Sparse System Matrices Survey Taxonomy
- Sparse Parameter Estimation and System Identification
  - Constrained Optimization for Sparse System Identification ★ (5 papers)
  - [0] Learning linear state-space models with sparse system matrices (Anon et al., 2026) View paper
  - [1] Learning linear dynamical systems under convex constraints (Hemant Tyagi, 2023) View paper
  - [32] Sparse system identification by low-rank approximation (Vides, 2021) View paper
  - [41] Data-driven sparse system identification (Salar Fattahi, 2018) View paper
  - [49] Sample complexity of sparse system identification problem (Salar Fattahi, 2018) View paper
  - Bayesian Sparse Parameter Estimation (3 papers)
  - [5] Sparse Bayesian Estimation of Parameters in Linear-Gaussian State-Space Models (Elvira, 2023) View paper
  - [7] Parameter Estimation in Sparse Linear-Gaussian State-Space Models via Reversible Jump Markov Chain Monte Carlo (Benjamin Cox, 2022) View paper
  - [30] Sparse Bayesian deep learning for dynamic system identification (Zhou Hongpeng, 2022) View paper
  - Robust Identification Under Adversarial Disturbances (2 papers)
  - [17] Learning of Dynamical Systems under Adversarial Attacks (Han Feng, 2021) View paper
  - [26] Learning of Dynamical Systems under Adversarial Attacks - Null Space Property Perspective (Han Feng, 2022) View paper
  - High-Dimensional and Structured System Identification (3 papers)
  - [9] System identification under general norms for linear parameter varying state-space systems via sparse matrix methods (Matthew Harker, 2022) View paper
  - [16] System Identification of High-Dimensional Linear Dynamical Systems With Serially Correlated Output Noise Components (Jiahe Lin, 2020) View paper
  - [20] High-dimensional linear state space models for dynamic microbial interaction networks (Iris Chen, 2017) View paper
- State and Input Estimation with Sparsity Constraints
  - Sparse Initial State and Input Estimation (2 papers)
  - [6] Sparse Initial State Estimation Algorithms (Geethu Joseph, 2024) View paper
  - [22] State and Sparse Input Estimation in Linear Dynamical Systems Using Low-Dimensional Measurements (Rupam kalyan chakraborty, 2025) View paper
  - Kalman Filtering and Smoothing with Sparsity (3 papers)

- [10] Sparse Kalman Filter-Based Channel Estimation for RIS-Aided Millimeter Wave Multiple-Input Multiple-Output Systems (Jing Zhang, 2023) View paper
- [35] Sparse/robust estimation and kalman smoothing with nonsmooth log-concave densities: Modeling, computation, and theory (Y AravkinAleksandr, 2013) View paper
- [45] Efficient estimation of compressible state-space models with application to calcium signal deconvolution (Kazemipour, 2016) View paper
- Reduced-Order and Sparse Representation for State Estimation (3 papers)
- [19] POD-Based Sparse Stochastic Estimation of Wind Turbine Blade Vibrations (Schena, 2025) View paper
- [46] Spatiotemporal system identification with continuous spatial maps and sparse estimation (Parham Aram, 2015) View paper
- [47] Blind deconvolution of sparse but filtered pulses with linear state space models (Nour Zalmai, 2016) View paper

- Sparse Graphical and Structured State-Space Models (5 papers)
  - [23] Sparse Graphical Linear Dynamical Systems (Chouzenoux, 2023) View paper
  - [28] Graphit: Iterative Reweighted â1 Algorithm for Sparse Graph Inference in State-Space Models (E Chouzenoux, 2023) View paper
  - [29] Multivariate Low-Rank State-Space Model with SPDE Approach for High-Dimensional Data (Rodeschini, 2025) View paper
  - [33] Sparse learning in Gaussian chain graphs for state space models (Lasse Petersen, 2018) View paper
  - [36] Structured Sparse Transition Matrices to Enable State Tracking in State-Space Models (Terzic, 2025) View paper
- Data-Driven Discovery and Nonlinear System Identification (3 papers)
  - [14] PySINDy: A comprehensive Python package for robust sparse system identification (Kaptanoglu, 2021) View paper
  - [15] GN-SINDy: Greedy sampling neural network in sparse identification of nonlinear partial differential equations (Ali Forootani, 2024) View paper
  - [40] Adaptive algorithms for sparse system identification (N. Kalouptsidis, 2011) View paper
- State Space Models with Neural and Deep Learning Components (4 papers)
  - [3] Sparse Learning for State Space Models on Mobile (X Shen, 2025) View paper
  - [13] SPikE-SSM: A Sparse, Precise, and Efficient Spiking State Space Model for Long Sequences Learning (Zhong Yan, 2024) View paper
  - [27] Sparsemamba: Ultra-Sparse State Space Models with Adaptive Sparsity for Efficient Hyperspectral Image Classification (å»ºå° å», 2025) View paper
  - [31] SpikingSSMs: Learning Long Sequences with Sparse and Parallel Spiking State Space Models (Shuaijie Shen, 2025) View paper
- Applications of Sparse State-Space Models
  - Signal Processing and Communication Systems (4 papers)
  - [4] Adaptive Bayesian filter with data-driven sparse state space model for seismic response estimation (Masaru Kitahara, 2024) View paper
  - [8] Smoothing for continuous dynamical state space models with sampled system coefficients based on sparse kernel learning (Nijia Qian, 2020) View paper
  - [37] A state space world for detecting and estimating events and learning sparse signal decompositions (Zalmai, 2017) View paper
  - [38] Two-Dimensional Augmented StateâSpace Approach with Applications to Sparse Representation of Radar Signatures (Kejiang Wu, 2019) View paper
  - Computer Vision and Motion Modeling (2 papers)
  - [12] Realistic full-body motion generation from sparse tracking with state space model (Kun Dong, 2024) View paper
  - [24] SSD-Poser: Avatar Pose Estimation with State Space Duality from Sparse Observations (Zhao Shu-ting, 2025) View paper
  - Anomaly Detection and Time-Series Analysis (2 papers)
  - [18] Sparsity-Constrained Vector Autoregressive Moving Average Models for Anomaly Detection of Complex Systems with Multisensory Signals (Meng Ma, 2024) View paper
  - [44] LSDSSMs: Infrared Small Target Detection Network Based on Low-Rank Sparse Decomposition State-Space Models (Yubing Lu, 2025) View paper
  - Control and Adaptive Systems (2 papers)
  - [39] Fast RLS Identification Leveraging the Linearized System Sparsity: Predictive Cost Adaptive Control for Quadrotors (Nguyen, 2025) View paper
  - [43] Learning Driver Behaviors Using A Gaussian Process Augmented State-Space Model (Anton Kullberg, 2020) View paper
  - Biological and Medical Systems (2 papers)
  - [42] Mathematical modeling of multiple pathways in colorectal carcinogenesis using dynamical systems with Kronecker structure (Saskia Haupt, 2020) View paper
  - [48] Challenges in evolutionary computing in the context of integrated bioinformatics (Sai Bharath Natte, 2025) View paper
- Theoretical Foundations and General Frameworks (6 papers)
  - [2] Parameter estimation in sparse state-space models (Cox, 2025) View paper
  - [11] Modal parameter estimation using the state space method (K. Liu, 1996) View paper
  - [21] Sparsity methods for systems and control (Nagahara, 2020) View paper
  - [25] Linear Dynamical Systems with Sparsity Constraints: Theory and Algorithms (Geethu Joseph, 2021) View paper
  - [34] Sparsity-Constrained Linear Dynamical Systems: From Compressed Sensing to Control Theory (Geethu Joseph, 2024) View paper
  - [50] Sparsity-Constrained Linear Dynamical Systems (Geethu Joseph, 2024) View paper

Narrative

Core task: Learning linear state-space models with sparse system matrices. The field addresses how to identify dynamical systems when the underlying transition or observation matrices contain only a small number of nonzero entries, a structure that arises naturally in many physical, biological, and engineered systems. The taxonomy organizes research into several major branches: Sparse Parameter Estimation and System Identification focuses on algorithms that directly recover sparse system matrices through regularized optimization or Bayesian inference, often employing convex relaxations or greedy methods; State and Input Estimation with Sparsity Constraints deals with filtering and smoothing problems where states or driving inputs are themselves sparse; Sparse Graphical and Structured State-Space Models emphasize network topology and conditional independence structures; Data-Driven Discovery and Nonlinear System Identification includes methods like SINDy that learn governing equations from data; State Space Models with Neural and Deep Learning Components integrate sparsity with modern neural architectures; Applications of Sparse State-Space Models demonstrate domain-specific uses in neuroscience, control, and biology; and Theoretical Foundations and General Frameworks provide sample complexity bounds and convergence guarantees. Representative works such as PySINDy[14] and Sparse Bayesian Estimation[5] illustrate the diversity of algorithmic approaches.

A particularly active line of work centers on constrained optimization techniques that balance model fidelity with sparsity-inducing penalties, trading off computational tractability against statistical efficiency. Convex Constrained Learning[1] and Low-Rank Approximation[32] exemplify methods that impose structural constraints during parameter estimation, while Data-Driven Sparse[41] and Sample Complexity Sparse[49] explore the interplay between data requirements and model complexity. Within this landscape, Sparse System Matrices[0] sits squarely in the Constrained Optimization for Sparse System Identification cluster, emphasizing principled optimization frameworks for recovering sparse transition matrices. Compared to neighbors like Convex Constrained Learning[1], which may prioritize convexity and scalability, Sparse System Matrices[0] likely addresses the specific challenges of enforcing exact or approximate sparsity patterns in linear dynamical systems, potentially offering tighter theoretical guarantees or more flexible constraint handling than earlier approaches such as Data-Driven Sparse[41].

Related Works in Same Category

The following **4 sibling papers** share the same taxonomy leaf node with the original paper:

1. Learning linear dynamical systems under convex constraints

Authors: Hemant Tyagi, Denis Efimov | **Year/Venue**: 2023 • arXiv.org | **URL**: View paper

Abstract

We consider the problem of finite-time identification of linear dynamical systems from T samples of a single trajectory. Recent results have predominantly focused on the setup where either no structural assumption is made on the system matrix $A^ \in \mathbb{R}^{n \times n}$, or specific structural assumptions (e.g. sparsity) are made on $A^$. We assume prior structural information on $A^$ is available, which can be captured in the form of a convex set $\mathcal{K}$ containing $A^$. For th...

Relationship Analysis

Both papers belong to the constrained optimization category for sparse system identification, using convex constraints and regularization to promote sparsity in linear state-space models. The original paper imposes Student's t-distribution priors on system matrices and uses an EM algorithm with RTS smoother for MAP estimation from noisy observations with hidden states, while the candidate paper focuses on convex constraint sets (including sparsity via $\ell1$ balls) and analyzes constrained least squares estimation with known state observations, deriving non-asymptotic error bounds via Talagrand's γ-functionals. The key difference is that the original addresses the harder problem of unobserved states requiring EM-based inference, whereas the candidate assumes observed (though noisy) states and provides theoretical sample complexity analysis for various convex constraint structures.

2. Sparse system identification by low-rank approximation

Authors: Vides, Fredy, Fredy Vides | **Year/Venue**: 2021 • arXiv.org | **URL**: View paper

Abstract

In this document, some general results in approximation theory and matrix analysis with applications to sparse identification of time series models and nonlinear discrete-time dynamical systems are presented. The aforementioned theoretical methods are translated into algorithms that can be used for sparse model identification of discrete-time dynamical systems, based on structured data measured from the systems. The approximation of the state-transition operators that are determined primarily by...

Relationship Analysis

Both papers belong to the constrained optimization category for sparse system identification, sharing the goal of learning sparse linear state-space models through regularization techniques. The candidate paper focuses on low-rank approximation methods for sparse parameter estimation, particularly addressing numerical and measurement noise through trajectory matrix decomposition. In contrast, the original paper employs sparsity-promoting priors (Student's t-distribution) within an EM framework to jointly estimate hidden states and system matrices while preserving topological structure, addressing the similarity transformation problem that classical methods face.

3. Data-driven sparse system identification

Authors: Salar Fattahi, Somayeh Sojoudi, S. Fattahi, S. Sojoudi | **Year/Venue**: 2018 | **URL**: View paper

Abstract

In this paper, we study the system identification porblem for sparse linear time-invariant systems. We propose a sparsity promoting Lasso-type estimator to identify the dynamics of the system with only a limited number of input-state data samples. Using contemporary results on high-dimensional statistics, we prove that $\Omega(k_{\max}\log(m+n))$ data samples are enough to reliably estimate the system dynamics, where n and m are the number of states and inputs, respectively, and $k_{\max}$ is th...

Relationship Analysis

Both papers belong to the constrained optimization for sparse system identification category, using sparsity-promoting techniques to learn linear state-space models. They overlap in addressing the sparse parameter estimation problem through regularization approaches, with both employing data-driven methods to recover sparse system matrices. The key difference is that the original paper uses a Bayesian framework with Student's t-distribution priors and an EM algorithm to handle hidden states and measurement noise, while the candidate paper employs a Lasso-type estimator with direct input-state data samples and focuses on exact sparsity structure recovery with sample complexity guarantees.

4. Sample complexity of sparse system identification problem

Authors: Salar Fattahi, Somayeh Sojoudi | **Year/Venue**: 2018 | **URL**: View paper

Abstract

In this paper, we study the system identification problem for sparse linear time-invariant systems. We propose a sparsity promoting block-regularized estimator to identify the dynamics of the system with only a limited number of input-state data samples. We characterize the properties of this estimator under high-dimensional scaling, where the growth rate of the system dimension is comparable to or even faster than that of the number of available sample trajectories. In particular, using contemp...

Relationship Analysis

Both papers belong to the constrained optimization category for sparse system identification, employing sparsity-promoting techniques to estimate linear state-space models. The candidate paper focuses on sample complexity analysis for sparse LTI systems using block-regularized ($\ell1/\ell\infty$) estimators with perfect state measurements, providing theoretical guarantees on the number of samples needed for exact sparsity recovery. The original paper differs by addressing the more challenging scenario where states are latent variables requiring EM-based inference, using Student's t-distribution priors instead of $\ell1$ regularization, and handling both process and measurement noise rather than assuming perfect state observations.

Contributions Analysis

Overall novelty summary. ```json { "paragraphs": ["The paper proposes an EM-based MAP estimation framework for learning linear state-space models with sparse system matrices by imposing sparsity-promoting priors. It resides in the 'Constrained Optimization for Sparse System Identification' leaf, which contains five papers addressing parameter estimation through regularization and convex constraints. This leaf sits within the broader 'Sparse Parameter Estimation and System Identification' branch, indicating a moderately populated research direction focused on optimization-based approaches to sparse system recovery. The taxonomy reveals this is an established but not overcrowded area, with neighboring leaves covering Bayesian methods, adversarial robustness, and high-dimensional structures.",

"The paper's leaf neighbors include Bayesian frameworks using MCMC for sparse inference and robust identification under adversarial disturbances, both of which offer alternative perspectives on handling sparsity constraints. The taxonomy structure shows clear boundaries: the paper's optimization-based approach contrasts with purely Bayesian methods in the sibling leaf and differs from state estimation techniques in parallel branches. Related directions include graphical state-space models emphasizing network topology and data-driven discovery methods for nonlinear systems, suggesting the paper occupies a niche balancing classical linear modeling with modern sparsity-inducing techniques. The scope notes clarify that the paper focuses on parameter estimation rather than state estimation or domain-specific applications.",

"Among thirty candidates examined, the EM algorithm contribution shows substantial prior work, with four of ten candidates providing overlapping methods. The convergence guarantee contribution similarly faces three refutable candidates from ten examined, indicating established theoretical frameworks in this space. The topological structure preservation contribution appears more distinctive, with zero refutable candidates among ten examined. These statistics suggest the core algorithmic and theoretical contributions build upon a well-developed foundation, while the structural preservation aspect may offer more novel insights. The limited search scope means these findings reflect top-semantic-match results rather than exhaustive coverage.",

"Given the search examined thirty candidates across three contributions, the paper appears to integrate established EM and convergence techniques with potentially novel topological preservation objectives. The taxonomy placement in a five-paper leaf within a fifty-paper field suggests moderate competition in this specific optimization-based sparse identification niche. The analysis captures semantic neighbors but does not cover all citation networks or recent preprints, leaving open questions about incremental versus transformative contributions relative to the full literature landscape."] } ```

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

Contribution 1: EM algorithm for learning LSSMs with sparse system matrices

Description: The authors propose an expectation-maximization algorithm that imposes sparsity-promoting priors (Student's t-distribution) on system matrices to learn linear state-space models with sparse structure. The method alternates between estimating hidden states using the RTS smoother and updating system matrices via block coordinate descent to maximize the joint posterior distribution.

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. GraphEM: EM algorithm for blind Kalman filtering under graphical sparsity constraints

URL: View paper

Prior Art Analysis

GraphEM Blind Kalman[66] demonstrates prior work on using EM algorithms for learning linear state-space models with sparsity constraints on system matrices. Both papers employ the EM framework where the E-step uses Kalman filtering/RTS smoothing to estimate hidden states, and the M-step updates system matrices. GraphEM[66] explicitly addresses sparse estimation of the state transition matrix A using $\ell 1$ (lasso) regularization, published in 2020, predating the original paper's submission to ICLR 2026. The candidate paper's approach of 'estimating the linear matrix operator in the state equation' with 'lasso regularization' directly parallels the original paper's contribution of learning 'system matrices with the sparsity constraint' using 'sparsity-promoting priors'.

Evidence

Evidence 1 - **Rationale**: Both papers use the same EM framework structure: E-step estimates hidden states using RTS smoother, M-step updates system matrices. This demonstrates the same algorithmic approach was already established in GraphEM[66]. - **Original**: in the expectation step, we use the rauch-tung-striebel (rts) smoother to give a closed-form update rule for the hidden states. in the maximization step, we leverage the block coordinate descent method to analytically update the system matrices in turn. - **Candidate**: the em algorithm alternates between a majoration step consisting in building an upper bound on the neg-log-likelihood function (e-step), and the minimization of this upper bound (m-step). in the context of state-space models with parameters θ, at each iteration i ∈ n of em method, one majorizes - lo...

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2. Towards Inversion-Free Sparse Bayesian Learning: A Universal Approach

URL: View paper

Brief Assessment

Inversion-Free Sparse Bayesian[63] focuses on sparse signal recovery in linear Gaussian models with computational efficiency improvements, not on learning linear state-space models with sparse system matrices from time-series data with hidden states.

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3. A state-space approach to sparse dynamic network reconstruction

URL: View paper

Prior Art Analysis

Sparse Network Reconstruction[65] demonstrates that EM algorithms for learning state-space models with sparsity-promoting priors were proposed prior to the original paper. The candidate paper presents an expectation-maximization framework that imposes sparsity constraints on system matrices through sparse Bayesian learning (SBL) with hierarchical priors. Both papers use the RTS smoother in the E-step for state estimation and employ iterative optimization in the M-step to update system matrices while promoting sparsity. The candidate's approach of using Student's t-distribution-like hierarchical priors (Gaussian with inverse-gamma hyperpriors) to enforce sparsity on state-space parameters directly parallels the original paper's methodology, indicating that this technical approach existed in prior work.

Evidence

Evidence 1 - **Rationale**: Both papers use EM algorithms to estimate state-space model parameters by treating hidden states as latent variables and maximizing posterior distributions with sparsity-promoting priors. - **Original**: we impose sparsity-promoting priors on system matrices to balance modeling error and model complexity. by taking hidden states of lssms as latent variables, we then explore the expectation-maximization (em) algorithm to derive a maximum a posteriori (map) estimate of both hidden states and system ma... - **Candidate**: in the setup of the sbl, we treat x0 as a given value. the complete-data likelihood function is p(xn|θ) ≜ p(xn,xn-1,...,x 1|θ) = p(xn|xn-1,θ) ⋯p(x2|x1,θ)p(x1,θ), where p(xk|xk-1,θ) = n(xk-axk-1 -buk-1,σ2i), k= 1,...,n . we rewrite the complete-data likelihood p(xn|θ) as follows, p(y|w; σ) = (2π)-n...

Evidence 2 - **Rationale**: Both papers employ the RTS/Kalman smoother in the E-step for state estimation and iteratively update system matrices in the M-step. - **Original**: in the expectation step, we use the rauch-tung-striebel (rts) smoother to give a closed-form update rule for the hidden states. in the maximization step, we leverage the block coordinate descent method to analytically update the system matrices in turn. - **Candidate**: the expectations in lemma 1 can be computed via kalman smoothers, listed in lemma 2. the expression in lemmar 1 implies that the maximization of q(θ,θ′) can be split into two parts: maximizing the part in terms of a,b,σ ; and update the estimations of x0 and r0 by ˆx0 = eθ′ (x0|yn), ˆr0 = eθ′ (x0xt ...

Evidence 3 - **Rationale**: Both papers formulate the learning problem as MAP estimation combining likelihood and prior distributions, using EM to maximize the posterior. - **Original**: following the bayes' rule, we can combine the marginal likelihood and prior functions to derive the joint posterior distribution of all the unknown variables as follows: p(θ|y)∝p(y|θ)| {z } marginal likelihood xp(θ)|{z} prior - **Candidate**: in the mstep, we perform the map to update θ: θi+1 = argmax θ q(θ,θi) + logp(w,γ), where p(w,γ) is the prior that depends on hyperparameter γ.

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4. Hierarchical MTC User Activity Detection and Channel Estimation With Unknown Spatial Covariance

URL: View paper

Brief Assessment

Hierarchical MTC Detection[67] addresses user activity detection and channel estimation in machine-type communications, not learning linear state-space models. The candidate uses EM for a completely different problem domain (wireless communications) with different objectives and mathematical formulations.

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5. Graphical inference in linear-Gaussian state-space models

URL: View paper

Prior Art Analysis

Graphical State Space[64] demonstrates that EM algorithms for learning linear-Gaussian state-space models with sparsity-promoting priors on system matrices existed prior to the original paper. Both papers use the expectation-maximization framework with the RTS smoother in the E-step and impose sparsity constraints on system matrices. The candidate paper explicitly describes using EM methodology with sparsity priors (including Student's t-distribution-like penalties) for estimating the transition matrix in linear-Gaussian SSMs, which directly overlaps with the original paper's claimed contribution.

Evidence

Evidence 1 - **Rationale**: Both papers propose EM algorithms for estimating system matrices in linear-Gaussian state-space models with sparsity constraints, demonstrating prior work exists. - **Original**: we impose sparsity-promoting priors on system matrices to balance modeling error and model complexity. by taking hidden states of lssms as latent variables, we then explore the expectation-maximization (em) algorithm to derive a maximum a posteriori (map) estimate of both hidden states and system ma... - **Candidate**: in this paper, we focus on the linear-gaussian model, arguably the most celebrated ssm, and particularly in the challenging task of estimating the transition matrix that encodes the markovian dependencies in the evolution of the multi-variate state. we introduce a novel perspective by relating this ...

Evidence 2 - **Rationale**: Both papers use the RTS smoother in the E-step and optimize system matrices in the M-step, showing the same algorithmic structure. - **Original**: in the expectation step, we use the rauch-tung-striebel (rts) smoother to give a closed-form update rule for the hidden states. in the maximization step, we leverage the block coordinate descent method to analytically update the system matrices in turn. - **Candidate**: at each iteration i∈n, the expectation function q(a; a(i)) given in (24) is first computed in the e-step. this function is created by running the kalman filter followed by the rts smoother with the state matrix set to the estimate of the previous iteration, i.e., equals to a(i). we then construct q(a;...

Evidence 3 - **Rationale**: Both papers combine likelihood and sparsity-promoting priors using Bayes' rule to derive MAP estimates, demonstrating the same methodological approach. - **Original**: to learn lssms with sparse system matrices, we impose sparsity-promoting priors on them to balance model complexity and modeling error. following the bayes' rule, we can combine the marginal likelihood and prior functions to derive the joint posterior distribution of all the unknown variables. - **Candidate**: graphem aims at providing the maximum a posteriori (map) estimator of a. more specifically, let us denote the posterior of the unknown parameter, p(a|y1:k), where the hidden states have been marginalized. it is direct to show, using bayes rule and the (strictly increasing) logarithmic function, that ...

Evidence 4 - **Rationale**: Both papers use sparsity-promoting priors (Student's t in original, Laplace/ℓ1 in candidate) to enforce sparsity on system matrices, showing similar prior work exists. - **Original**: here, we impose the student'st-distribution prior on the system matricesa,b,c, anddto promote model sparsity, because it can be sharply peaked at zero compared to other priors - **Candidate**: an immediate idea would be to define f as the ℓ0 norm of a, that counts the number of non-zero entries of the matrix. however, this function is non-convex, non continuous, and it is associated to a improper law p(a), which is undesirable. instead, one prefers to choose for p(a), the proper, logconcav...

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6. A generalized GraphEM for sparse time-varying dynamical systems

URL: View paper

Prior Art Analysis

GraphEM Sparse[61] demonstrates that EM algorithms for learning linear state-space models with sparsity-promoting priors on system matrices existed prior to the original paper. The candidate paper presents an EM framework that imposes sparsity constraints on system matrices through ℓ1-regularization and uses the RTS smoother for state estimation, followed by optimization of system matrices. Both papers address the same fundamental problem: learning sparse system matrices in linear state-space models using EM with sparsity-promoting techniques. The candidate's approach of alternating between E-step (RTS smoothing) and M-step (parameter optimization with sparsity constraints) directly parallels the original paper's methodology.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly describe using EM framework for joint parameter estimation and smoothing in linear systems with sparsity constraints, demonstrating that this approach existed in GraphEM Sparse[61]. - **Original**: we impose sparsity-promoting priors on system matrices to balance modeling error and model complexity. by taking hidden states of lssms as latent variables, we then explore the expectation-maximization (em) algorithm to derive a maximum a posteriori (map) estimate of both hidden states and system ma... - **Candidate**: we consider the problem of joint parameter estimation and smoothing in structured linear systems using the expectation maximization (em) framework. specifically, we explore how partially known sparsity structures in the estimation model can be leveraged to improve the computation speed and performanc...

Evidence 2 - **Rationale**: GraphEM Sparse[61] describes the same two-step process: using RTS smoother in E-step and optimizing system matrices with sparsity constraints in M-step, establishing prior work on this methodology. - **Original**: in the expectation step, we use the rauch-tung-striebel (rts) smoother to give a closed-form update rule for the hidden states. in the maximization step, we leverage the block coordinate descent method to analytically update the system matrices in turn. - **Candidate**: in the lti setting, em methods tend to utilize the closed-form solutions to the resulting optimization problems in the model parameters ξ ≜ {a,c,q,r}. when considering unknown sparsity in ξ, it has been suggested to add an ℓ1-regularization term in the m-step (chouzenoux and elvira, 2020), referred ...

Evidence 3 - **Rationale**: GraphEM Sparse[61] explicitly discusses EM algorithms for learning sparse system matrices and addresses sparsity enforcement, showing this was an established research direction before the original paper. - **Original**: leveraging sparsity-promoting techniques, we propose an algorithm to learn lssms with sparse system matrices from noisy observations. following the global convergence theorem (luenberger et al., 1984), we also demonstrate that the proposed algorithm is guaranteed to converge to a local maximum or sa... - **Candidate**: the em algorithm consists of first computing a smoothing posterior given θ(i) (the e-step), and subsequently updating θ(i) →θ(i+1) by minimizing (6) (the m-step), as summarized in algorithm 1. in this basic formulation, the em: (i) does not straightforwardly generalize to the ltv setting; (ii) does n...

Evidence 4 - **Rationale**: GraphEM Sparse[61] describes computing MAP estimates with sparsity-promoting regularization (ℓ1) in the context of learning system matrices, demonstrating this approach predates the original paper's contribution. - **Original**: to learn lssms with sparse system matrices, we impose sparsity-promoting priors on them to balance model complexity and modeling error. following the bayes' rule, we can combine the marginal likelihood and prior functions to derive the joint posterior distribution of all the unknown variables. - **Candidate**: the graphem in (chouzenoux and elvira, 2020) is also developed in an lti setting, computing the maximum a posteriori (map) estimate of a subject to an ℓ1 regularization. as in the original algorithm, we here use the linear parameterization a = mat(θa) ∈rd(x)xd(x), let ¯a= mat(¯θa) ∈rd(x)xd(x) for co...

7. Data-driven discovery of linear dynamical systems from noisy data

URL: View paper

Brief Assessment

The candidate paper context is too fragmentary to assess novelty. Only disconnected phrases about 'expectation-maximization framework' and 'sparsitypromoting technique' are visible, without sufficient detail to determine whether it addresses the same problem or uses similar methods.

8. Parameter estimation in sparse state-space models

URL: View paper

Brief Assessment

Sparse Parameter Estimation[2] focuses on sparse Bayesian estimation using reversible jump MCMC for linear-Gaussian state-space models, not EM algorithms with sparsity-promoting priors like Student's t-distribution.

9. Efficient estimation of compressible state-space models with application to calcium signal deconvolution

URL: View paper

Brief Assessment

Calcium Signal Deconvolution[45] focuses on sparse innovations (state transitions) in compressible state-space models for signal deconvolution, not on learning sparse system matrices themselves. The sparsity constraint applies to different model components.

10. Graphit: Iterative Reweighted â1 Algorithm for Sparse Graph Inference in State-Space Models

URL: View paper

Brief Assessment

Graphit[28] focuses on estimating the transition matrix A in linear-Gaussian state-space models using an MM algorithm with non-convex penalties. The original paper addresses a broader problem of learning all system matrices (A, B, C, D) with Student's t-distribution priors and uses RTS smoother with block coordinate descent, which is technically distinct from Graphit's approach.

Contribution 2: Global convergence guarantee for the proposed algorithm

Description: The authors provide a theoretical convergence analysis demonstrating that their algorithm is guaranteed to converge to a local maximum or saddle point of the posterior distribution, leveraging the Global Convergence Theorem.

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. Convergence of EM image reconstruction algorithms with Gibbs smoothing

URL: View paper

Brief Assessment

EM Gibbs Smoothing[54] focuses on image reconstruction in emission tomography with Gibbs priors, not on learning linear state-space models with sparse system matrices. The convergence analysis applies to a different problem domain and algorithm structure.

2. The Information Bottleneck EM Algorithm

URL: View paper

Brief Assessment

Information Bottleneck EM[53] focuses on learning Bayesian networks with hidden variables using information bottleneck principles, not linear state-space models with sparse system matrices. The convergence analysis contexts differ fundamentally.

3. Global Convergence of EM Algorithm for Mixtures of Two Component Linear Regression

URL: View paper

Brief Assessment

EM Linear Regression[52] analyzes convergence for mixture of two-component linear regression models, not linear state-space models with sparse system matrices. The problem domains, model structures, and algorithmic contexts differ fundamentally.

4. Efficient EM optimization exploiting parallel local sampling strategy and Bayesian optimization for microwave applications

URL: View paper

Brief Assessment

Parallel Bayesian EM[58] focuses on electromagnetic optimization for microwave design applications, not on theoretical convergence guarantees for expectation-maximization algorithms applied to posterior distributions in state-space models.

5. The EM algorithm and extensions

URL: View paper

Brief Assessment

EM Extensions[55] is a textbook providing general theory on EM algorithm convergence, not a research paper proposing a specific algorithm for learning linear state-space models with sparse system matrices. The original paper applies the Global Convergence Theorem to their specific MAP estimation framework for sparse LSSMs, which is a distinct application context.

6. Convergence results for the EM approach to mixtures of experts architectures

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.

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7. Convergence of the expectation-maximization algorithm through discrete-time lyapunov stability theory

URL: View paper

Brief Assessment

EM Lyapunov Convergence[51] analyzes convergence of the standard EM algorithm using Lyapunov stability theory, while the original paper proposes a novel EM-based algorithm for learning sparse linear state-space models with sparsity-promoting priors. The convergence analysis contexts differ fundamentally.

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8. Regularized EM Algorithms: A Unified Framework and Statistical Guarantees

URL: View paper

Prior Art Analysis

Regularized EM Framework[57] demonstrates prior work establishing global convergence guarantees for EM-based algorithms to local maxima or saddle points. The candidate paper explicitly proves that their regularized EM algorithm converges to local maxima or saddle points of the posterior distribution using the Global Convergence Theorem, which is the same theoretical framework and convergence target claimed by the original paper. Both papers leverage the Global Convergence Theorem from Luenberger et al. (1984) to establish convergence to local maxima or saddle points, showing that this type of convergence guarantee was already established in the literature before the original paper's submission.

Evidence

Evidence 1 - **Rationale**: The candidate paper discusses convergence properties of EM algorithms and references prior work (Balakrishnan et al. 2014) that established convergence results for EM, showing that convergence analysis of EM algorithms was an active area of research before the original paper. - **Original**: by alternately performing the expectation and maximization steps until convergence, the proposed algorithm can determine the sparse system matrices of lssms from noisy observations. - **Candidate**: the popular em algorithm and its variants, is a much used algorithmic tool; yet our rigorous unders tanding of its performance is highly incomplete. recently, work in balakrishnan et al. (2014) has demonstrated that for an important class of problems, em exhibits linear local convergence.

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9. Online Inference for Mixture Model of Streaming Graph Signals With Sparse Excitation

URL: View paper

Prior Art Analysis

Streaming Graph Mixture[60] demonstrates prior work on convergence guarantees for EM algorithms to stationary points of posterior distributions. The candidate paper explicitly proves that their EM algorithm converges to a stationary point of the MAP problem using similar theoretical frameworks. Both papers leverage convergence theorems to establish that their EM-based algorithms reach local maxima or saddle points, with the candidate providing this guarantee in 2022 (before the original paper's 2026 submission).

Evidence

Evidence 1 - **Rationale**: Both papers claim convergence to stationary points (local maxima or saddle points) of posterior/MAP distributions for their EM algorithms, demonstrating similar theoretical guarantees. - **Original**: based on the global convergence theorem, we further demonstrate that the proposed learning algorithm yields a sequence converging to a local maximum or saddle point of the joint posterior distribution. - **Candidate**: we show that the proposed algorithms converge to a stationary point of the maximum-a-posterior (map) problem.

Evidence 2 - **Rationale**: The candidate explicitly states convergence to stationary points of MAP problems for their EM algorithm, which is the same type of guarantee claimed by the original paper. - **Original**: following the global convergence theorem (luenberger et al., 1984), we also demonstrate that the proposed algorithm is guaranteed to converge to a local maximum or saddle point of the posterior distribution composed of marginal likelihood and prior functions. - **Candidate**: we design an expectation-maximization (em) algorithm with a unique low-rank plus sparse prior derived from low pass signal property. we propose a novel online em algorithm for inference from streaming data. as an example, we extend the online algorithm to detect if the signals are generated from an ...

Evidence 3 - **Rationale**: Both papers provide formal convergence theorems for their EM algorithms, establishing that the generated sequences converge to stationary points with similar mathematical frameworks. - **Original**: theorem 3.3.from any valid initialization pointθ 0, the limit point of the sequence{θ k}∞ k=1 generated viaθ k+1 =a θk is a local maximum (or saddle point) of equation 6. - **Candidate**: proposition 1 consider the sequence {θk}k≥0 generated by algorithm 1. the following holds: 1) the regularized log-likelihood value is non-decreasing: l(θk+1) ≥l(θk), ∀k≥0. (19) 2) if the gradient w.r.t. θ for the difference function d(θ|˜θ) is l-lipschitz continuous, then for any kmax ≥1, min k=1,.....

Evidence 4 - **Rationale**: Both papers explicitly reference convergence theorems and provide formal proofs that their EM algorithms converge to stationary points, demonstrating similar theoretical contributions. - **Original**: leveraging the global convergence theorem (luenberger et al., 1984), we can demonstrate that the proposed algorithm is globally convergent. theorem 3.3.from any valid initialization pointθ 0, the limit point of the sequence{θ k}∞ k=1 generated viaθ k+1 =a θk is a local maximum (or saddle point) of... - **Candidate**: note that if l′(θ; θ -θ) ≤0 for all θ ∈t, then θ is a stationary point to the map problem (7). as such, algorithm 1 finds a stationary point to (7) at a sublinear rate. a key challenge in our analysis is that the map problem (7) is nonsmooth due to the sparse/low-rank priors in (8). we achieve the pr...

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10. Alternating Bregman projections and convergence of the EM algorithm

URL: View paper

Prior Art Analysis

Alternating Bregman EM[59] demonstrates prior work on convergence guarantees for EM-type algorithms to local maxima or saddle points. The candidate paper proves that alternating Bregman projection sequences converge to local maxima or saddle points of posterior distributions using the Global Convergence Theorem, which is the same theoretical framework claimed as novel by the original paper. Both papers establish convergence to local maxima or saddle points using similar theoretical foundations, with the candidate providing this result in 2025 for Bregman projection methods that encompass EM algorithms.

Evidence

Evidence 1 - **Rationale**: The candidate establishes global convergence for alternating Bregman projection sequences, which directly applies to EM algorithms. This demonstrates that convergence guarantees for such algorithms were proven before the original paper's work. - **Original**: following the global convergence theorem (luenberger et al., 1984), we also demonstrate that the proposed algorithm is guaranteed to converge to a local maximum or saddle point of the posterior distribution composed of marginal likelihood and prior functions. - **Candidate**: theorem 7.1. (global convergence) . let ak, bk be a bregman alternating sequence with gap (k∗, r∗). suppose the rl-angle condition and rl-three-point inequality are satisfied at every (b∗, a∗) ∈ k∗. then the sequence bk $\in \overleftarrow{p}$b $\circ \overrightarrow{p}$a(bk-1) converges.

Contribution 3: Preservation of topological structure in learned system matrices

Description: Unlike classical learning algorithms that only learn system matrices up to a similarity transformation, the proposed algorithm preserves the inherent topological structure among variables by restricting the similarity transformation to generalized permutation matrices through sparsity constraints, making the learned models more interpretable.

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. Hâ distributed control for large systems and its application to coupled inverted pendulum

URL: View paper

Brief Assessment

Distributed Coupled Pendulum[72] focuses on distributed H∞ control for large-scale systems with known system matrices and topological structure, not on learning algorithms that preserve structure through sparsity constraints.

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2. Refined convergence and topology learning for decentralized sgd with heterogeneous data

URL: View paper

Brief Assessment

Decentralized SGD Topology[76] focuses on learning communication topologies for distributed optimization algorithms to handle data heterogeneity across nodes, not on learning system matrices of linear state-space models with sparsity constraints to preserve topological structure among variables.

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3. GSSF: Generalized Structural Sparse Function for Deep Cross-Modal Metric Learning

URL: View paper

Brief Assessment

GSSF Cross-Modal[69] focuses on cross-modal metric learning for vision-language tasks using structured sparse distance functions, not on learning linear state-space models with topological structure preservation through sparsity constraints on system matrices.

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4. Subspace learning via Hessian regularized latent representation learning with -norm constraint: unsupervised feature selection

URL: View paper

Brief Assessment

Hessian Regularized Learning[74] focuses on unsupervised feature selection via Hessian regularization for preserving topological structure of data manifolds, not on learning linear state-space models with sparse system matrices through similarity transformation constraints.

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5. Sparse representation for restoring images by exploiting topological structure of graph of patches

URL: View paper

Brief Assessment

Graph Patches Restoration[70] focuses on image restoration using graph-based sparse representations of image patches, not on learning linear state-space models or preserving topological structure in system matrices through sparsity constraints.

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6. Online Graph Topology Learning via Time-Vertex Adaptive Filters: From Theory to Cardiac Fibrillation

URL: View paper

Brief Assessment

Cardiac Topology Learning[68] focuses on dynamic graph topology estimation from time-varying signals using adaptive filtering methods in the graph signal processing domain, not on learning linear state-space models with sparsity constraints to preserve topological structure through similarity transformation restrictions.

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7. Towards high-precision data modeling of SHM measurements using an improved sparse Bayesian learning scheme with strong generalization ability

URL: View paper

Brief Assessment

SHM Sparse Bayesian[73] focuses on data modeling and forecasting for structural health monitoring measurements using sparse Bayesian learning, not on preserving topological structure among variables in system matrices through similarity transformation constraints.

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8. On the Role of Sparsity and DAG Constraints for Learning Linear DAGs

URL: View paper

Brief Assessment

Sparsity DAG Constraints[71] focuses on learning DAG structures for graphical models using sparsity and DAG constraints, not on preserving topological structure in state-space system matrices through similarity transformations. The paper addresses a different problem domain (graphical structure learning vs. linear state-space model identification).

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9. An Explainable Probabilistic Model for Health Monitoring of Concrete Dam via Optimized Sparse Bayesian Learning and Sensitivity Analysis

URL: View paper

Brief Assessment

Concrete Dam Monitoring[75] focuses on dam health monitoring using sparse Bayesian learning for radial displacement and seepage prediction, not on learning linear state-space models or preserving topological structure in system matrices through similarity transformation constraints.

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10. Higher Order Transformers With Kronecker-Structured Attention

URL: View paper

Brief Assessment

Kronecker Attention Transformers[77] focuses on factorized attention mechanisms for multiway tensor data in transformers, not on learning linear state-space models with sparse system matrices or preserving topological structure through similarity transformation constraints.

Appendix: Text Similarity Detection

Textual similarity detection checked 34 papers and found 2 similarity segment(s) across 2 paper(s).

The following **2 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. Graphical inference in linear-Gaussian state-space models

Detected in: Contribution: contribution_1

⚠ **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.

2. GraphEM: EM algorithm for blind Kalman filtering under graphical sparsity constraints

Detected in: Contribution: contribution_1

⚠ **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] Learning linear state-space models with sparse system matrices View paper
- [1] Learning linear dynamical systems under convex constraints View paper
- [2] Parameter estimation in sparse state-space models View paper
- [3] Sparse Learning for State Space Models on Mobile View paper
- [4] Adaptive Bayesian filter with data-driven sparse state space model for seismic response estimation View paper
- [5] Sparse Bayesian Estimation of Parameters in Linear-Gaussian State-Space Models View paper
- [6] Sparse Initial State Estimation Algorithms View paper
- [7] Parameter Estimation in Sparse Linear-Gaussian State-Space Models via Reversible Jump Markov Chain Monte Carlo View paper
- [8] Smoothing for continuous dynamical state space models with sampled system coefficients based on sparse kernel learning View paper
- [9] System identification under general norms for linear parameter varying state-space systems via sparse matrix methods View paper
- [10] Sparse Kalman Filter-Based Channel Estimation for RIS-Aided Millimeter Wave Multiple-Input Multiple-Output Systems View paper
- [11] Modal parameter estimation using the state space method View paper
- [12] Realistic full-body motion generation from sparse tracking with state space model View paper
- [13] SPikE-SSM: A Sparse, Precise, and Efficient Spiking State Space Model for Long Sequences Learning View paper
- [14] PySINDy: A comprehensive Python package for robust sparse system identification View paper
- [15] GN-SINDy: Greedy sampling neural network in sparse identification of nonlinear partial differential equations View paper
- [16] System Identification of High-Dimensional Linear Dynamical Systems With Serially Correlated Output Noise Components View paper
- [17] Learning of Dynamical Systems under Adversarial Attacks View paper
- [18] Sparsity-Constrained Vector Autoregressive Moving Average Models for Anomaly Detection of Complex Systems with Multisensory Signals View paper
- [19] POD-Based Sparse Stochastic Estimation of Wind Turbine Blade Vibrations View paper
- [20] High-dimensional linear state space models for dynamic microbial interaction networks View paper
- [21] Sparsity methods for systems and control View paper
- [22] State and Sparse Input Estimation in Linear Dynamical Systems Using Low-Dimensional Measurements View paper
- [23] Sparse Graphical Linear Dynamical Systems View paper
- [24] SSD-Poser: Avatar Pose Estimation with State Space Duality from Sparse Observations View paper
- [25] Linear Dynamical Systems with Sparsity Constraints: Theory and Algorithms View paper
- [26] Learning of Dynamical Systems under Adversarial Attacks - Null Space Property Perspective View paper
- [27] Sparsemamba: Ultra-Sparse State Space Models with Adaptive Sparsity for Efficient Hyperspectral Image Classification View paper
- [28] Graphit: Iterative Reweighted â1 Algorithm for Sparse Graph Inference in State-Space Models View paper
- [29] Multivariate Low-Rank State-Space Model with SPDE Approach for High-Dimensional Data View paper
- [30] Sparse Bayesian deep learning for dynamic system identification View paper
- [31] SpikingSSMs: Learning Long Sequences with Sparse and Parallel Spiking State Space Models View paper
- [32] Sparse system identification by low-rank approximation View paper
- [33] Sparse learning in Gaussian chain graphs for state space models View paper
- [34] Sparsity-Constrained Linear Dynamical Systems: From Compressed Sensing to Control Theory View paper
- [35] Sparse/robust estimation and kalman smoothing with nonsmooth log-concave densities: Modeling, computation, and theory View paper
- [36] Structured Sparse Transition Matrices to Enable State Tracking in State-Space Models View paper
- [37] A state space world for detecting and estimating events and learning sparse signal decompositions View paper
- [38] Two-Dimensional Augmented StateâSpace Approach with Applications to Sparse Representation of Radar Signatures View paper
- [39] Fast RLS Identification Leveraging the Linearized System Sparsity: Predictive Cost Adaptive Control for Quadrotors View paper
- [40] Adaptive algorithms for sparse system identification View paper
- [41] Data-driven sparse system identification View paper
- [42] Mathematical modeling of multiple pathways in colorectal carcinogenesis using dynamical systems with Kronecker structure View paper
- [43] Learning Driver Behaviors Using A Gaussian Process Augmented State-Space Model View paper
- [44] LSDSSMs: Infrared Small Target Detection Network Based on Low-Rank Sparse Decomposition State-Space Models View paper

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