

Breaking the gridlock in Mixture-of-Experts: Consistent and Efficient algorithms

Ashok Vardhan Makkuva

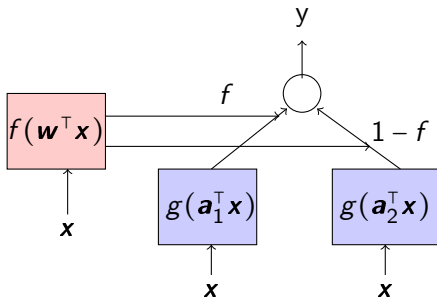
University of Illinois at Urbana-Champaign

Joint work with
Sewoong Oh, Sreeram Kannan, Pramod Viswanath



Mixture-of-Experts (MoE)

- Jacobs, Jordan, Nowlan and Hinton, 1991



f = sigmoid, g = linear, tanh, ReLU, leakyReLU

Motivation-I: Modern relevance of MoE

- Outrageously large neural networks

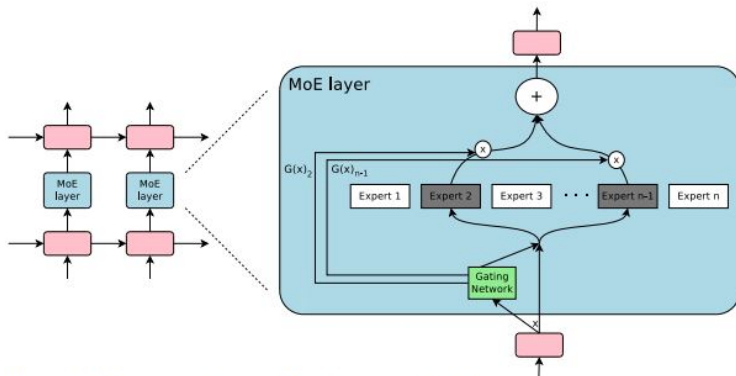


Figure 1: A Mixture of Experts (MoE) layer embedded within a recurrent language model. In this case, the sparse gating function selects two experts to perform computations. Their outputs are modulated by the outputs of the gating network.

Motivation-II: Gated RNNs

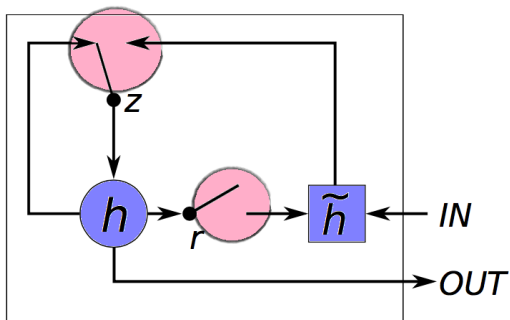
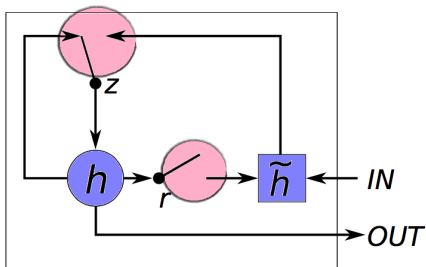


Figure: Gated Recurrent Unit (GRU)

Key features:

- **Gating** mechanism
- Long term memory

Motivation-II: GRU



- **Gates:** $z_t, r_t \in [0, 1]^d$ depend on the input x_t and the past h_{t-1}
- **States:** $h_t, \tilde{h}_t \in \mathbb{R}^d$

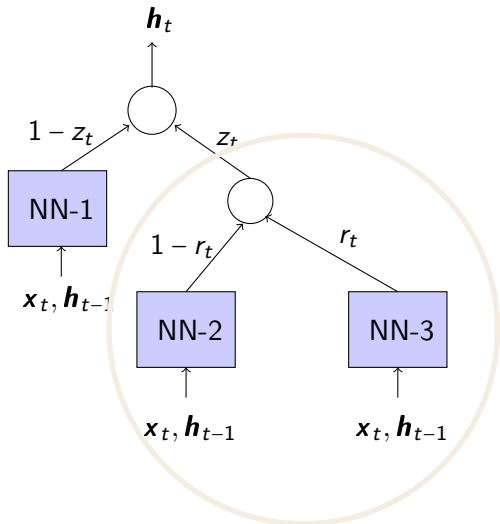
Update equations for each t :

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

$$\tilde{h}_t = f(Ax_t + r_t \odot Bh_{t-1})$$

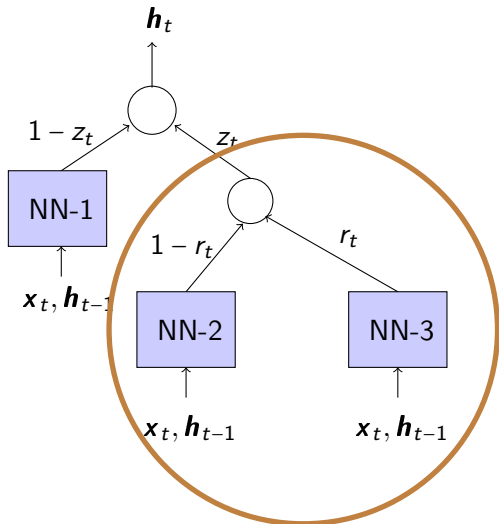
MoE: Building blocks of GRU

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot (1 - r_t) \odot f(Ax_t) + z_t \odot r_t \odot f(Ax_t + Bh_{t-1})$$



MoE: Building blocks of GRU

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot (1 - r_t) \odot f(Ax_t) + z_t \odot r_t \odot f(Ax_t + Bh_{t-1})$$



What is known about MoE?

Adaptive mixtures of local experts

RA Jacobs, MI Jordan, SJ Nowlan, GE Hinton
Neural computation 3 (1), 79-87

3663

1991

Sharing clusters among related groups: Hierarchical Dirichlet processes

YW Teh, MI Jordan, MJ Beal, DM Blei
Advances in neural information processing systems, 1385-1392

3273

2005

Hierarchical mixtures of experts and the EM algorithm

MI Jordan, RA Jacobs
Neural computation 6 (2), 181-214

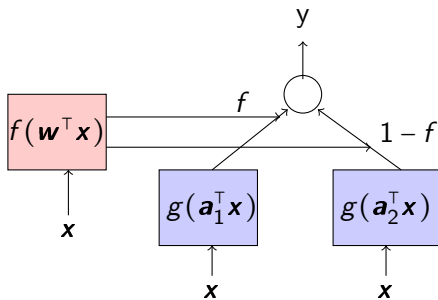
3090

1994

- No provable learning algorithms for parameters¹ ☹️

¹20 years of MoE, MoE: a literature survey

Open problem for 25+ years



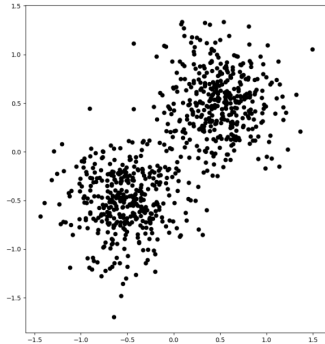
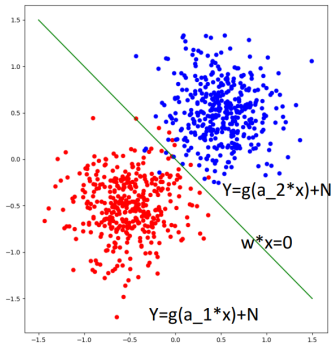
$$\Leftrightarrow P_{y|x} = f(\mathbf{w}^\top \mathbf{x}) \cdot \mathcal{N}(y|g(\mathbf{a}_1^\top \mathbf{x}), \sigma^2) + (1 - f(\mathbf{w}^\top \mathbf{x})) \cdot \mathcal{N}(y|g(\mathbf{a}_2^\top \mathbf{x}), \sigma^2)$$

Open question

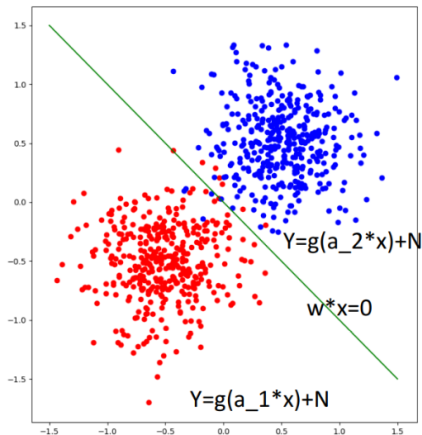
Given n i.i.d. samples $(\mathbf{x}^{(i)}, y^{(i)})$, does there exist an efficient learning algorithm with provable theoretical guarantees to learn the regressors $\mathbf{a}_1, \mathbf{a}_2$ and the gating parameter \mathbf{w} ?

Modular structure

Mixture of classification (w) and regression (a_1, a_2) problems



Key observation



Key observation

If we know the regressors, learning the gating parameter is easy and vice-versa. How to break the gridlock?

Breaking the gridlock: An overview

Recall the model for MoE:

$$P_{y|x} = f(\mathbf{w}^\top \mathbf{x}) \cdot \mathcal{N}(y|g(\mathbf{a}_1^\top \mathbf{x}), \sigma^2) + (1 - f(\mathbf{w}^\top \mathbf{x})) \cdot \mathcal{N}(y|g(\mathbf{a}_2^\top \mathbf{x}), \sigma^2)$$

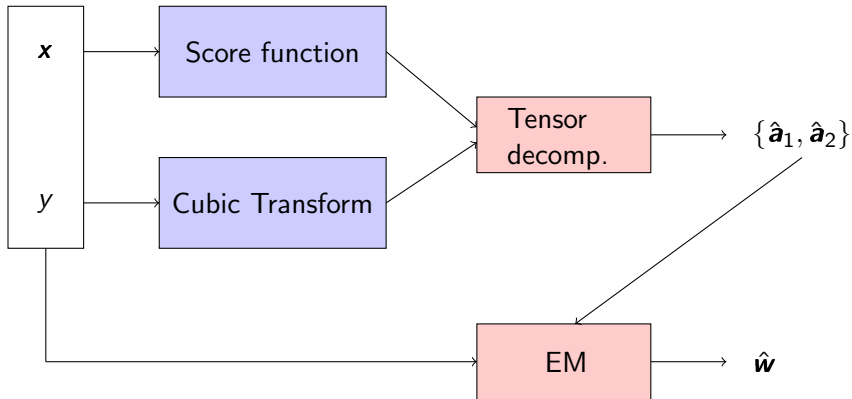
Main message

We propose a novel algorithm with first recoverable guarantees

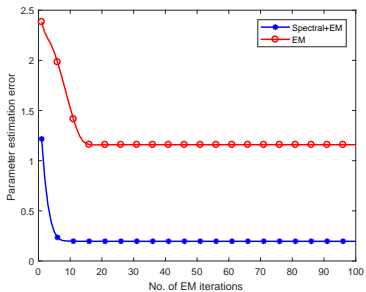
- We learn $(\mathbf{a}_1, \mathbf{a}_2)$ and \mathbf{w} *separately*
- First recover $(\mathbf{a}_1, \mathbf{a}_2)$ without knowing \mathbf{w} at all
- Later learn \mathbf{w} using traditional methods like EM
- Global consistency guarantees (population setting)

Algorithm

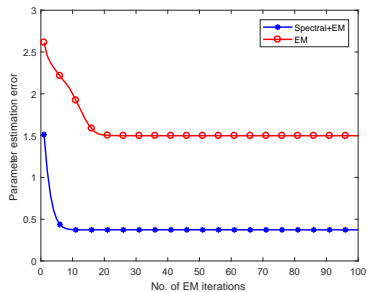
Samples



Comparison with EM



(a) 3 mixtures



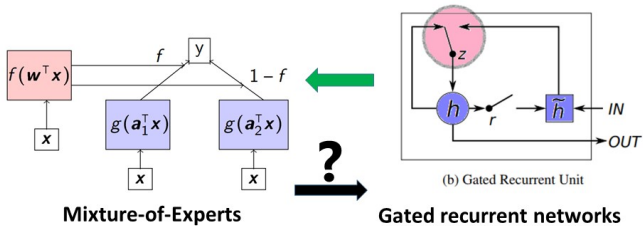
(b) 4 mixtures

Figure: Plot of parameter estimation error

Summary

- **Algorithmic innovation:** First provably consistent algorithms for MoE in 25+ years
- **Global convergence:** Our algorithms work with global initializations

Conclusion



1. Theoretical understanding ✓
2. Novel algorithms ✓

1. Theoretical understanding?
2. Algorithms?

Poster #210

Thank you!

Poster #210

Thank you!