

# DriftMoE: A Mixture of Experts Approach to Handle **Concept Drifts**

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#### **PROBLEM & MOTIVATION**

- Concept drift challenges
- On-stationary streams
- Resource constraints

#### **Current Limitations**

- False positive detection
- Coarse adaptation
- Simple voting schemes

### **SOLUTION OVERVIEW**

#### **DriftMoE Framework:**

- Online MoE architecture
- Co-training approach
- Neural router + experts

#### **Two Variants:**

- MoE-Data (multi-class)
- MoE-Task (one-vs-rest)

# **KEY FEATURES & ARCHITECTURE**

- Multi-hot correctness
- Mask training
- Cooperative feedback
- Symbiotic learning
- Resource efficiency:
- Cooperative feedback 12 vs 100+ experts

#### **Technical Details:**

- Hoeffding Tree experts
- BCE loss optimization
- Online mini-batches

# $(x_1, y_1) \rightarrow (x_2, y_2) \rightarrow (x_2, y_3) \rightarrow ... \rightarrow concept drift$ Expert Correctness Mask Prequential update Expert pool

 $\hat{y}_t$ 

Non-Stationary Data Streams

#### **EXPERIMENTAL SETUP**

Category	Stream	Instances	Features	Classes
Synthetic	LED (Abrupt)	1,000,000	24	10
	LED (Gradual)	1,000,000	24	10
	SEA (Abrupt)	1,000,000	3	2
	SEA (Gradual)	1,000,000	3	2
	$RBF_m$	1,000,000	10	5
	$RBF_f$	1,000,000	10	5
Real	Airlines	539,383	7	2
	Electricty	45,312	8	2
	Cover Type	581,012	54	7

- 9 benchmarks (6+3 real)
- Prequential evaluation
- 5 state-of-art baseline
- Accuracy, Kappa metrics

#### **KEY FINDINGS**

#### Summary:

- ✓ Competitive accuracy
- 8x fewer resources
- Fast drift adaptation

#### **Future Directions:**

- Uncertainty routing
- Dynamic allocation
- Cost-sensitive losses

**RESULTS & PERFORMANCE** 

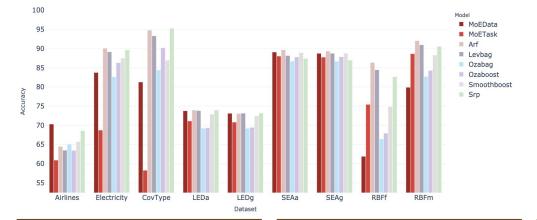


Table 1: DriftMoE Performance Summary

Dataset	MoEData	MoETask	
Airlines	$70.33 \pm 0.18$	$60.92 \pm 0.01$	
CovType	$81.28 \pm 0.75$	$58.28 \pm 0.31$	
Electricity	$83.76 \pm 0.45$	$68.73 \pm 0.85$	
$\mathrm{LED}_a$	$73.77\pm0.18$	$71.11 \pm 0.54$	
$\mathrm{LED}_g$	$\textbf{73.11}\pm\textbf{0.11}$	$70.82 \pm 0.38$	
$\mathrm{RBF}_f$	$61.90 \pm 0.20$	$\textbf{75.45}\pm\textbf{0.11}$	
$\mathrm{RBF}_m$	$79.89 \pm 0.48$	$88.65\pm0.07$	
$SEA_a$	$89.09\pm0.05$	$88.04 \pm 0.09$	
$\mathrm{SEA}_g$	$88.74\pm0.05$	$87.76 \pm 0.04$	

## **CONCLUSIONS**

#### **Main Contributions:**

- First streaming MoE for concept drift
- Novel co-training framework
- Multi-hot feedback
- Competitive performance with fewer resources

## Impact:

- Scalable online learning
- Efficient drift handling

# **USE CASES**

#### Applications:

- IoT data streams
- Financial markets
- Social media feeds •
- Edge computing

- Deployment: • Resource-constrained
- environments
  - Real-time inference · Adaptive edge devices
  - Streaming analytics

#### **FUNDING**



