Remember Past, Anticipate Future:

Learning Continual Multimodal Misinformation Detectors

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Motivation

New Task **Continual Multimodal Misinformation Detection**

On real-world online social media, **new events always continually emerge**, which renders MMD models trained on offline data ineffective in practical scenarios.

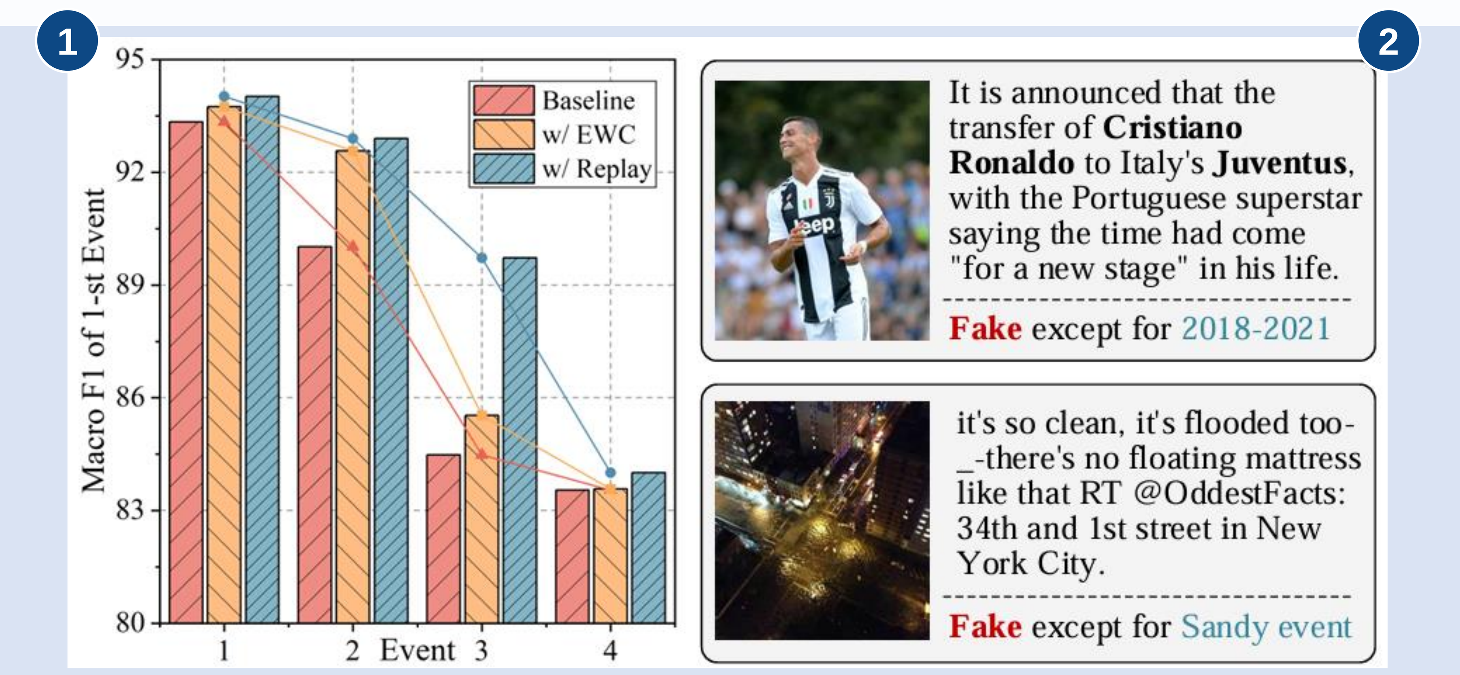
➢ **Challenge 1: Past Knowledge Forgetting**

When facing data streams, especially large-scale data, training on new data consistently causes the detection performance of MMD models to decrease on past data.

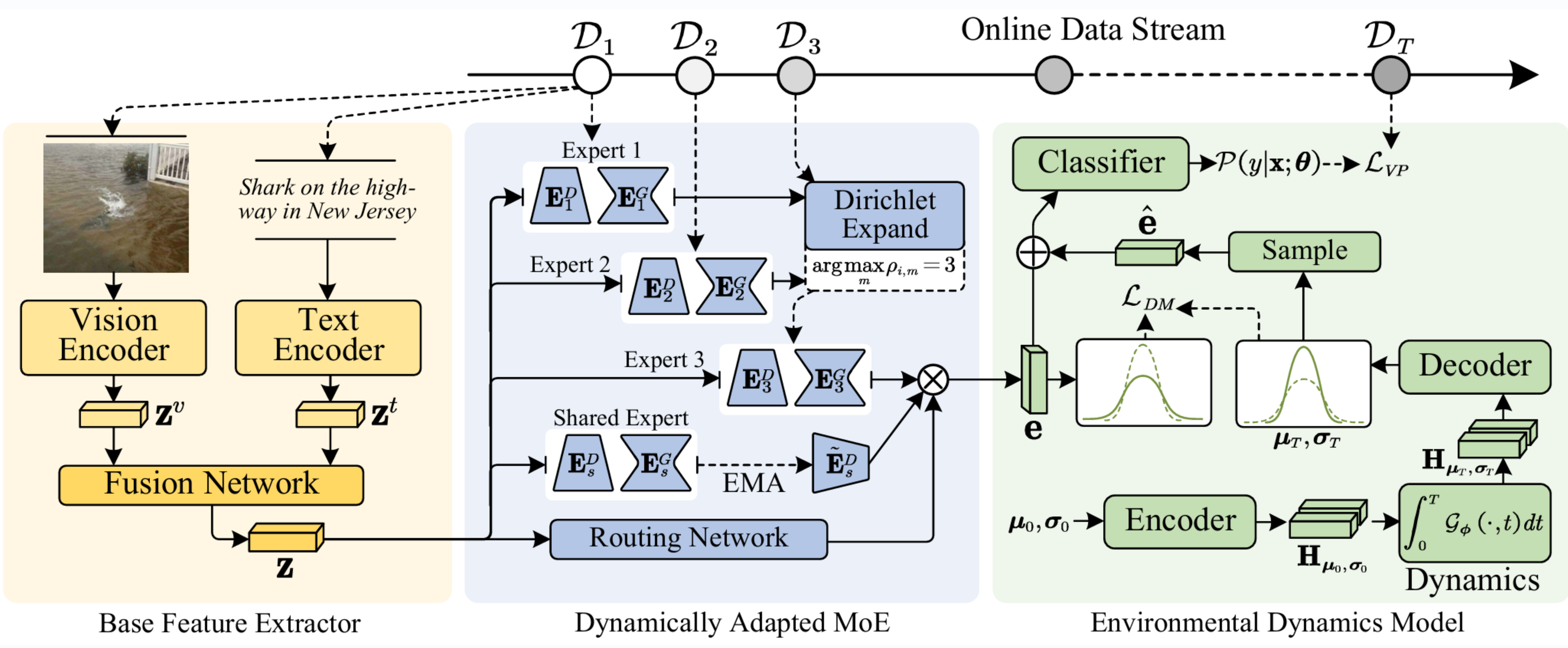
➢ **Challenge 2: Social Environment Evolving**

In online scenarios, the social environment consistently changes over time, which leads to a gradual evolution of the data distributions, especially fake ones.

Empirical evidence



Our Proposed Method: DAEDCMD



To address these two challenges, we propose a new framework **DAEDCMD**, which aims to restore the knowledge of past data and simultaneously learn the dynamic environmental distribution. Specifically, DAEDCMD consists of three following modules.

Module 1: Base Feature Extractor

This module extracts **semantic features** of image/text content and fusing them into a multimodal feature. It can be replaced by various SOTA MMD methods, *e.g.*, BMR.

Module 2: Dynamically Adapted MoE

Generally, this module aims to alleviate the knowledge forgetting issue by employing an MoE-based model, which consists of a Dirichlet process mixture-based method to dynamically expand experts and an exponential moving average optimized event-shared expert.

➢ **Key Part A: Event-shared & Event-specific Experts**

✓ Specifically, we initialize a **event-shared** expert and *M* **event-specific** experts, and each expert contains a **discriminator part** and a variational **generator part**. The discriminator is implemented as a LoRA model and the generator is structured as a variational autoencoder, which includes an encoder and a decoder to reconstruct the input.

➢ **Key Part B: Dirichlet Expert Expanding**

✓ Dynamically expand the number of experts

$$-\log\rho_{i,m} \propto \begin{cases} -\log\sum\rho_{<i,m} - \log\mathbb{P}(y_i|\mathbf{z}_i;\mathbf{E}_m^D) \\ \qquad\qquad -\log\mathbb{P}(\mathbf{z}_i;\mathbf{E}_m^G), \\ -\log\lambda - \log\mathbb{P}(y_i|\mathbf{z}_i;\mathbf{E}_s^D) \\ \qquad\qquad -\log\mathbb{P}(\mathbf{z}_i;\mathbf{E}_s^G), \end{cases} = \begin{cases} -\log\sum\rho_{<i,m} + \ell_{CE}([\mathbf{z}_i\mathbf{E}_m^D;\hat{\mathbf{e}}]\mathbf{W}_C, y_i) \\ \qquad\qquad + \mathcal{L}_{VG}, \\ -\log\lambda + \ell_{CE}([\mathbf{z}_i\mathbf{E}_s^D;\hat{\mathbf{e}}]\mathbf{W}_C, y_i) + \mathcal{L}_{VG}, \end{cases}$$

Module 3: Environmental Dynamics Model

To predict the dynamics, we train a **dynamics model** to predict the environmental distribution (implemented by a **Gaussian distribution**) of future samples, and sample an environmental feature for veracity prediction.

$$\mathcal{L}_{DM} = \frac{1}{K}\int_0^K \|\hat{\boldsymbol{\mu}}_\tau - \boldsymbol{\mu}_\tau\|_2^2 + \|\hat{\boldsymbol{\sigma}}_\tau - \boldsymbol{\sigma}_\tau\|_2^2 \mathrm{d}t,$$

$$\textbf{s.t.}\quad \mathrm{H}_{\boldsymbol{\mu}_0} = \boldsymbol{\mu}_0\mathrm{W}_E,\ \mathrm{H}_{\boldsymbol{\sigma}_0} = \boldsymbol{\sigma}_0\mathrm{W}_E,\quad \hat{\boldsymbol{\mu}}_\tau = \mathrm{H}_{\boldsymbol{\mu}_\tau}\mathrm{W}_D,\ \hat{\boldsymbol{\sigma}}_\tau = \mathrm{H}_{\boldsymbol{\sigma}_\tau}\mathrm{W}_D,$$

$$\mathrm{H}_{\boldsymbol{\mu}_\tau} = \mathrm{H}_{\boldsymbol{\mu}_0} + \int_0^\tau \mathcal{G}_{\phi_\mu}(\mathrm{H}_{\boldsymbol{\mu}}, t)\mathrm{d}t,\ \mathrm{H}_{\boldsymbol{\sigma}_\tau} = \mathrm{H}_{\boldsymbol{\sigma}_0} + \int_0^\tau \mathcal{G}_{\phi_\sigma}(\mathrm{H}_{\boldsymbol{\sigma}}, t)\mathrm{d}t,$$

Experimental Results

Model	Dataset: *GossipCop* [31]				Dataset: *Weibo* [18]				Dataset: *Twitter* [1]			
	Accuracy	F1	$F1_{real}$	$F1_{fake}$	Accuracy	F1	$F1_{real}$	$F1_{fake}$	Accuracy	F1	$F1_{real}$	$F1_{fake}$
Base [6, 13]	84.52±0.7	73.32±1.3	90.61±0.5	57.02±1.8	87.98±0.7	87.94±0.7	87.27±0.8	88.60±0.7	62.20±1.8	62.10±1.8	60.98±1.9	63.22±1.8
+ EWC [12, 21]	84.91±0.6	74.95±2.2	90.69±0.5	58.81±1.6	88.46±0.5	88.41±0.5	87.64±0.6	89.19±0.5	64.13±1.1	63.73±1.4	60.68±1.8	66.78±2.1
+ Replay [22]	84.90±1.2	74.81±2.2	90.68±0.7	59.00±1.7	88.53±0.8	88.47±0.8	87.65±0.8	89.30±0.9	63.90±1.8	63.82±1.7	62.58±1.2	65.05±1.4
+ LoRAMoE [9]	84.89±1.2	74.91±0.8	90.67±0.9	59.18±1.4	88.60±0.9	88.55±0.9	87.75±1.0	89.34±0.9	64.64±1.3	64.56±1.3	62.91±1.8	66.21±1.9
+ **DAEDCMD**	**86.21**±0.8	**76.13**±0.5	**91.64**±0.6	**60.63**±1.0	**90.07**±0.6	**90.05**±0.6	**89.67**±0.6	**90.50**±0.6	**67.66**±1.7	**67.44**±1.5	**65.64**±1.3	**69.24**±2.0
SAFE [46]	84.31±1.4	73.93±0.6	90.38±1.1	57.47±1.2	87.30±1.2	87.16±1.2	85.82±1.1	88.50±1.1	62.46±1.8	61.69±2.4	58.49±1.7	66.89±2.1
+ EWC [12, 21]	84.63±0.7	74.48±0.7	90.85±1.5	59.12±1.6	87.90±0.9	87.88±0.9	87.43±0.9	88.32±0.8	63.25±1.4	62.90±1.4	60.33±1.9	65.48±1.9
+ Replay [22]	84.81±0.7	74.68±1.1	90.54±0.6	58.76±2.2	88.67±1.0	88.60±1.0	87.72±1.0	89.49±1.0	64.01±0.6	62.73±1.2	59.73±2.0	67.73±1.9
+ LoRAMoE [9]	84.66±0.8	75.06±0.8	90.54±0.6	58.59±1.1	88.67±0.8	88.64±0.9	88.04±0.7	89.23±0.4	64.73±1.6	64.19±1.4	59.80±1.3	67.58±1.6
+ **DAEDCMD**	**86.72**±0.4	**76.48**±1.2	**91.99**±0.2	**60.98**±1.3	**90.46**±0.2	**90.45**±0.2	**90.19**±0.3	**90.72**±0.1	**68.08**±1.8	**67.36**±1.5	**63.65**±1.3	**71.07**±1.9
MCAN [40]	84.54±1.9	73.31±0.8	90.87±0.4	60.19±1.3	87.71±1.0	87.61±1.0	86.47±1.3	88.75±0.8	62.98±2.0	60.58±1.2	58.27±1.4	68.90±2.1
+ EWC [12, 21]	85.21±0.8	73.44±1.2	90.84±0.9	57.40±2.2	88.40±0.6	88.38±0.6	87.98±0.6	88.79±0.6	64.37±1.0	64.26±0.6	60.59±1.3	66.98±2.1
+ Replay [22]	85.19±0.7	73.25±1.0	90.72±1.0	58.78±2.1	88.53±0.7	88.51±0.7	87.97±0.9	89.05±0.7	64.46±1.0	64.01±1.3	60.02±1.4	67.01±1.3
+ LoRAMoE [9]	84.88±0.8	74.38±0.6	90.89±0.5	59.30±0.8	87.99±0.7	87.94±0.7	87.17±0.8	88.70±0.6	64.64±1.4	64.63±1.3	60.62±1.3	67.68±2.0
+ **DAEDCMD**	**86.37**±0.7	**76.33**±0.8	**91.74**±0.5	**60.91**±1.3	**90.10**±0.8	**90.07**±0.8	**89.58**±0.9	**90.58**±0.7	**67.43**±0.9	**66.99**±0.9	**63.81**±1.3	**71.18**±1.3
CAFE [3]	84.03±1.3	74.46±0.8	90.09±1.0	59.21±1.5	87.81±1.0	87.75±1.0	86.94±1.2	88.55±0.8	61.77±1.5	60.96±1.3	58.62±1.5	66.31±2.0
+ EWC [12, 21]	84.63±1.2	75.30±0.8	90.48±0.9	60.13±0.9	88.50±1.0	88.42±1.1	87.43±1.3	89.40±0.8	63.83±1.2	63.19±1.7	59.30±1.5	67.07±1.8
+ Replay [22]	84.59±1.0	74.65±1.4	90.54±0.9	59.76±1.8	88.03±0.5	88.01±0.5	87.55±0.6	88.47±0.5	65.06±1.2	64.75±1.0	61.67±1.7	67.84±1.9
+ LoRAMoE [9]	84.87±0.7	74.00±1.6	90.60±0.3	59.67±2.5	88.60±0.6	88.52±0.6	87.53±0.8	89.50±0.9	64.53±1.8	62.08±1.4	60.26±1.5	67.89±1.5
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BMR [42]	83.92±1.6	73.64±1.0	90.60±1.2	58.10±2.0	87.54±0.8	87.50±0.8	86.84±0.9	88.16±0.8	62.22±1.2	61.31±1.2	58.39±1.8	67.24±1.9
+ EWC [12, 21]	84.45±1.0	74.58±0.9	90.22±0.8	59.63±2.2	88.40±0.8	88.34±0.8	87.52±0.6	89.16±1.0	63.49±1.5	63.23±1.4	60.12±1.5	66.34±2.0
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+ **DAEDCMD**	**86.13**±0.6	**76.31**±0.7	**91.56**±0.4	**61.07**±1.2	**89.86**±0.8	**89.84**±0.8	**89.47**±1.1	**90.20**±0.5	**67.36**±1.3	**67.23**±1.3	**66.08**±1.4	**69.38**±1.5
GAMED [30]	84.28±1.2	73.84±1.1	90.78±0.9	59.61±2.1	87.29±0.9	87.24±0.9	87.48±1.0	87.98±0.9	61.90±0.6	60.88±1.4	59.07±1.7	65.71±1.9
+ EWC [12, 21]	84.45±1.6	74.65±1.0	90.41±1.2	59.29±1.6	88.49±0.9	88.47±0.9	88.04±1.1	88.91±0.8	64.73±1.7	63.34±1.3	59.22±2.1	68.46±2.1
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+ **DAEDCMD**	**86.21**±1.0	**76.17**±0.7	**91.73**±0.5	**60.62**±1.0	**89.93**±0.7	**89.90**±0.7	**89.42**±0.9	**90.39**±0.5	**67.21**±1.7	**67.31**±1.3	**62.98**±1.7	**70.63**±1.5

➢ DAEDCMD **outperform** **six** MMD baselines and **three** continual learning methods across **three** datasets

Key Takeaways

➢ **New Task:** We focus on a new task named continual multimodal misinformation detection, and we argue that this task have two primary challenges: past knowledge forgetting and social environment evolving.

➢ **Method**: We propose a dynamically adapted MoE module to learn event-shared/specific experts, and dynamically expand them with a Dirichlet processing model. To learn the dynamics of social environment, we design a environmental dynamics model with a neural ordinary differential equation.

➢ **Experiments**: By comparing with baseline models, we have demonstrated the effectiveness of our model.

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