Memory-Guided Multi-View Multi-Domain Fake News Detection

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TKDE'22

220714 Chia-Chun Ho

Outline
of FND-CLIP

Introduction

Methodology

Experiments

Conclusion

Comments

Introduction

Fake News Detection

- The wide spread of fake news on social media has threatened both individuals and society.
- In the COVID-19 infodemic, thousands of fake news pieces have been widely spread around the world.
    - Caused social panic and weakened the effect of pandemic countermeasures.
- Automatic detection of fake news has been critical for sustainable and healthy development of news platforms.

Introduction

News Domains

- Most existing methods only focus on a single domain (e.g. politics).
- News pieces in different domains are inherently correlated in fact.
- Intuitively, simultaneously modeling multiple correlated news domains benefits fake news detection.

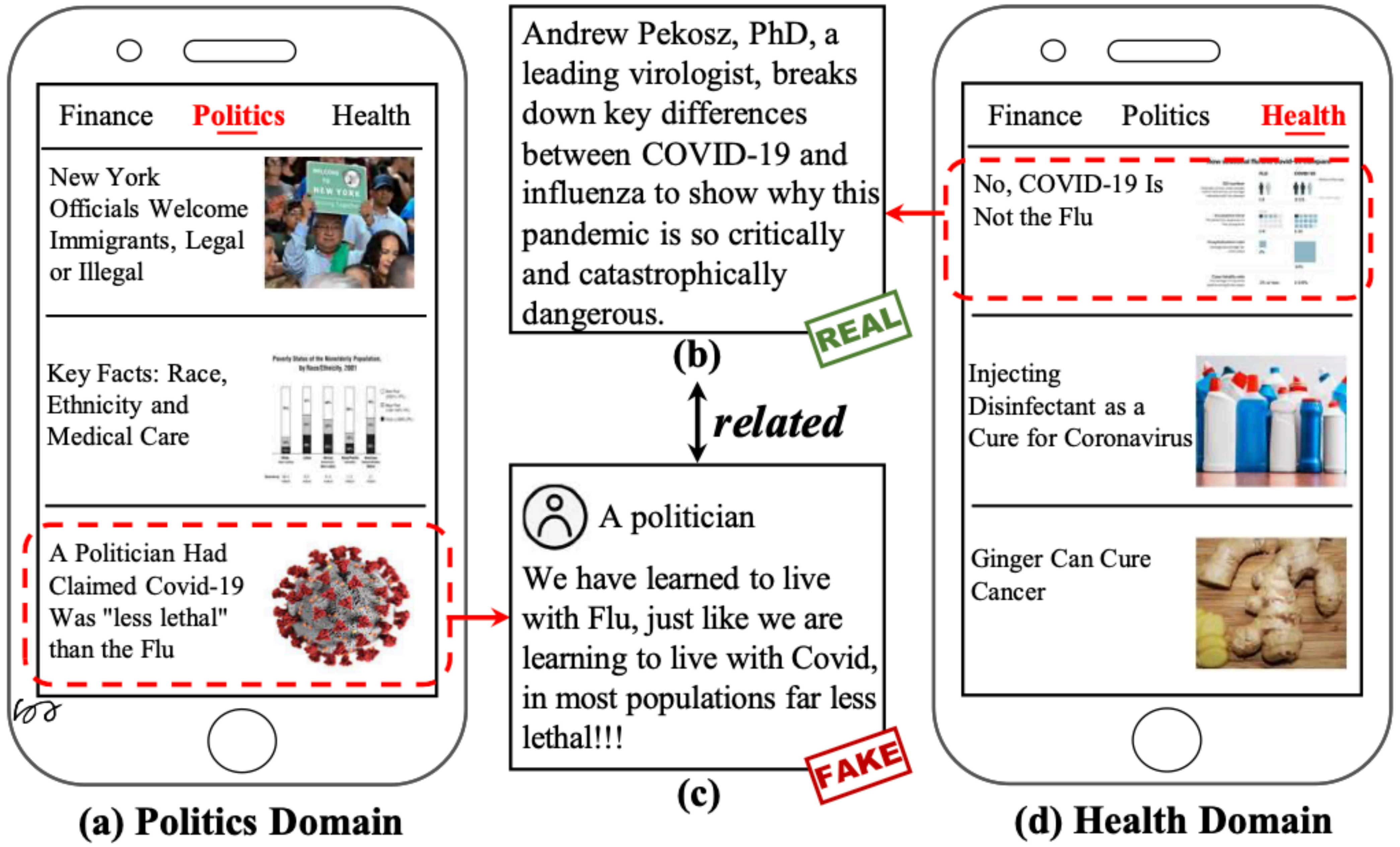
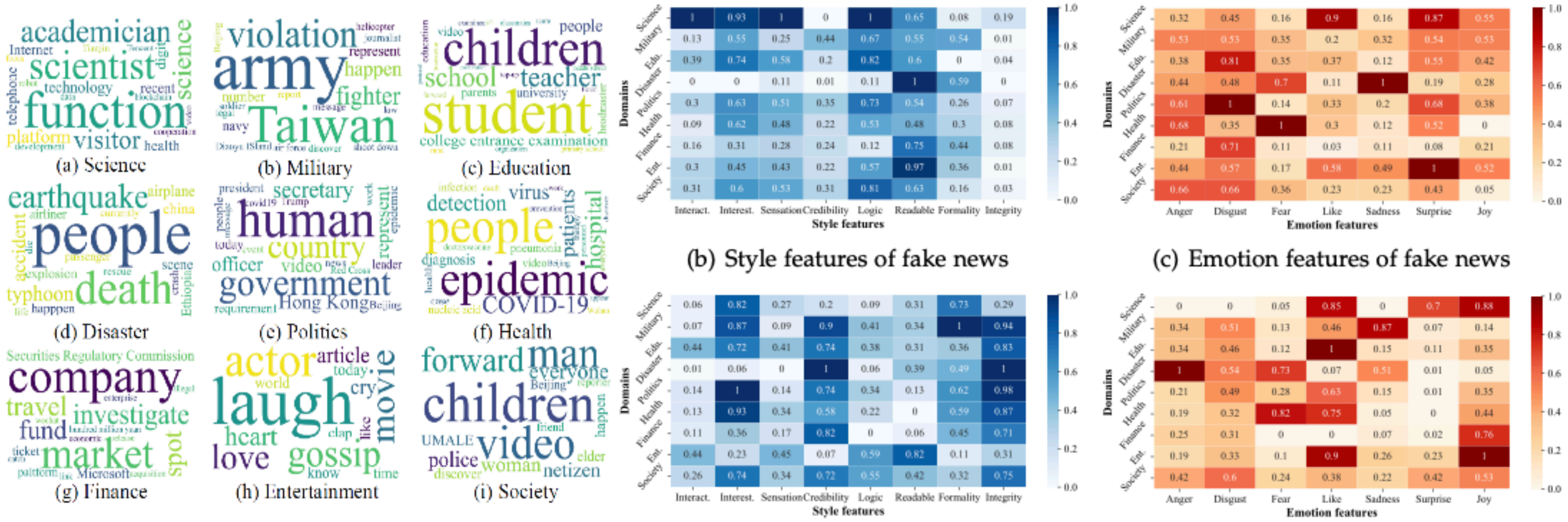


Fig. 1. An example of a real-world news platform with ***multiple news domains***. The news distributions vary from domain to domain, leading to the challenge of ***domain shift***. However, a news piece is a mixture of diverse elements which makes it relate to multiple news domains, e.g., the political news (c) is also related to the health news (b), leading to the challenge of ***domain labeling incompleteness***.

Introduction

Challenges of Multi-domain FND (1/2)



(a) Top 20 words in the nine domains (b) Style features of fake news (c) Emotion features of fake news (d) Style features of real news (e) Emotion features of real news

- Domain shift among multiple news domains.
  - Various news domains have significant domain discrepancies.
    - E.g. words, emotions, styles.
    - Distributions of aforementioned of various domains would be largely different.
  - The differences among domains are called domain shift.
    - It could seriously influence the effectiveness of joint training multi-domain data.
    - It's essential to propose well-designed multi-domain models to alleviate the influence of it.

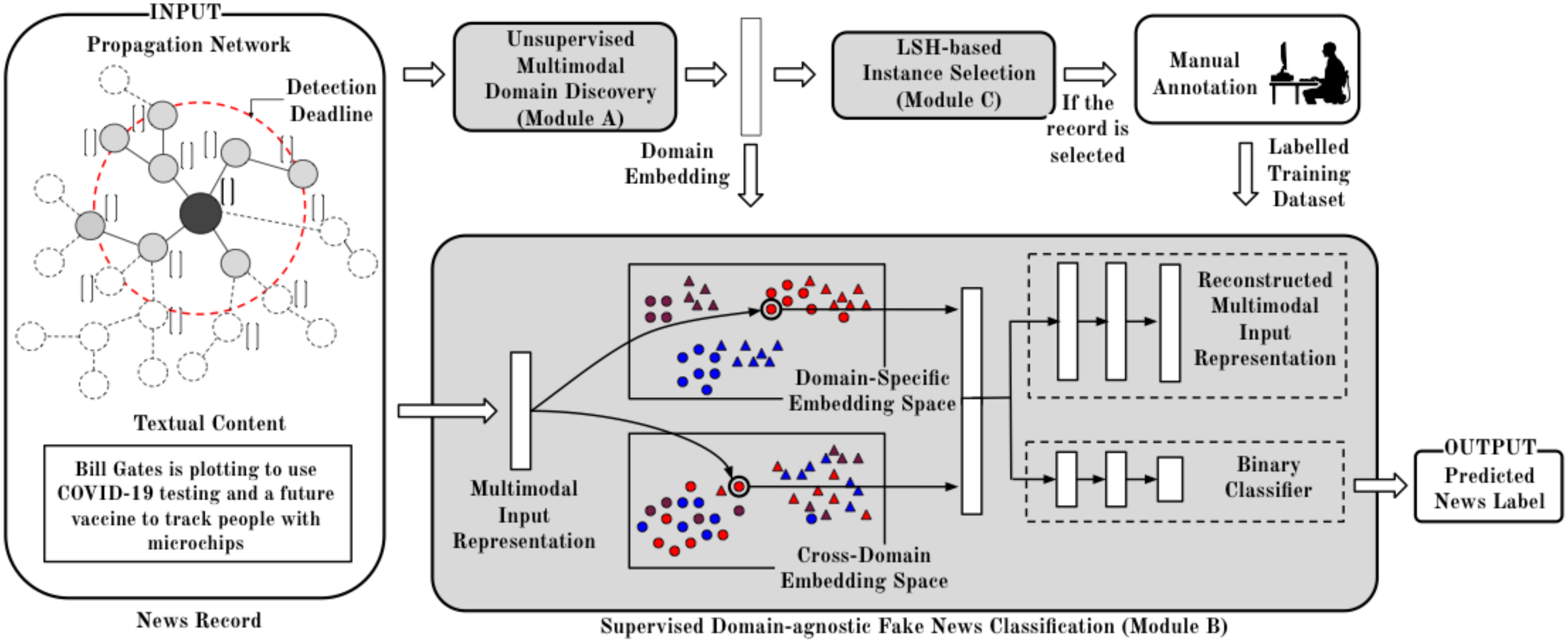
Introduction

Challenges of Multi-domain FND (2/2)

- Domain labeling incompleteness for news pieces
  - A news piece is released in a single-domain (channel) in a real world news platform.
  - However, it's a mixture of diverse elements which makes it relate to multiple news domains.
    - Indicates a news piece could have multiple domain labels.
    - Completing the domain labels is important for building an accurate multi-domain fake news detection system.

Introduction

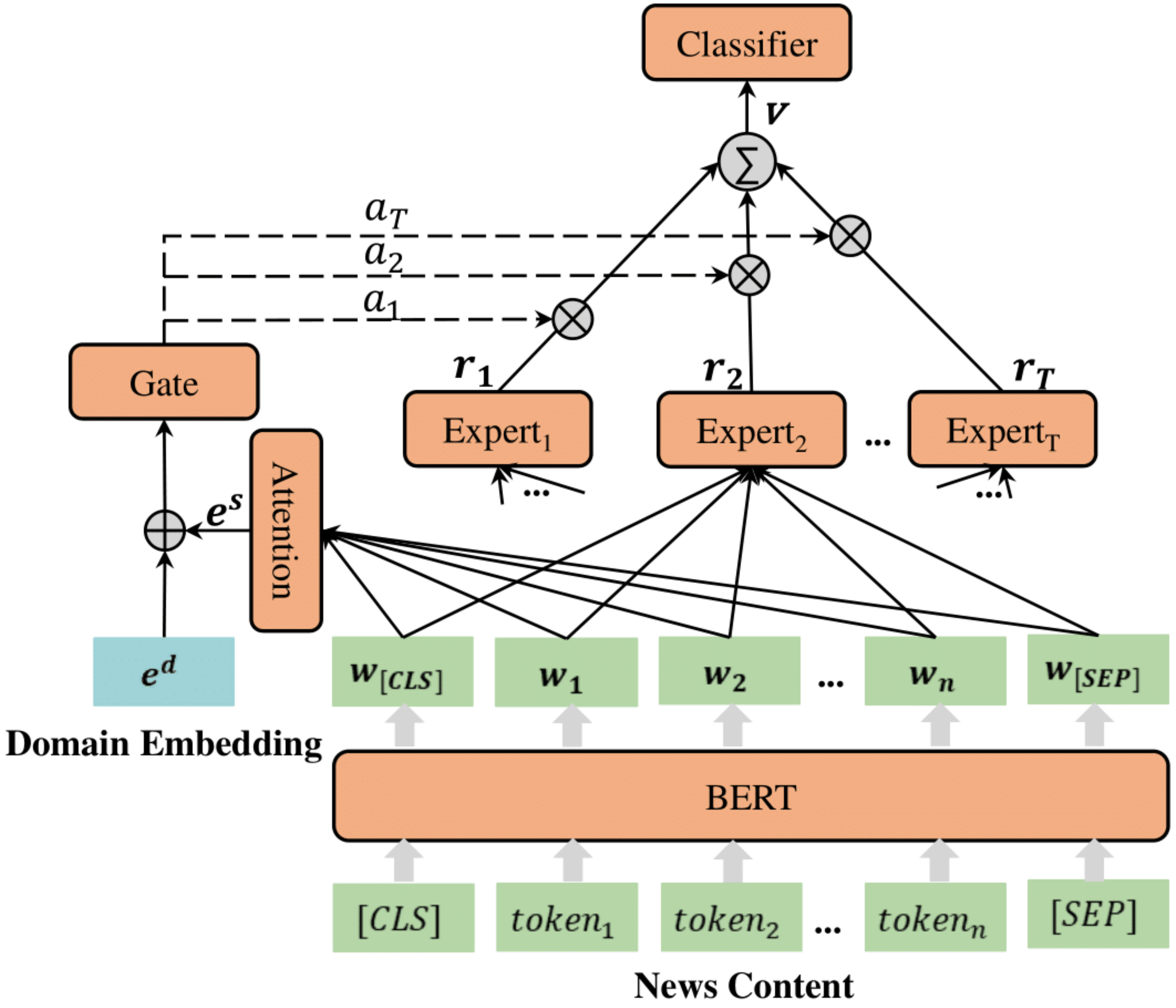
Embracing Domain Differences in Fake News (EDDFN*) (AAAI'21)

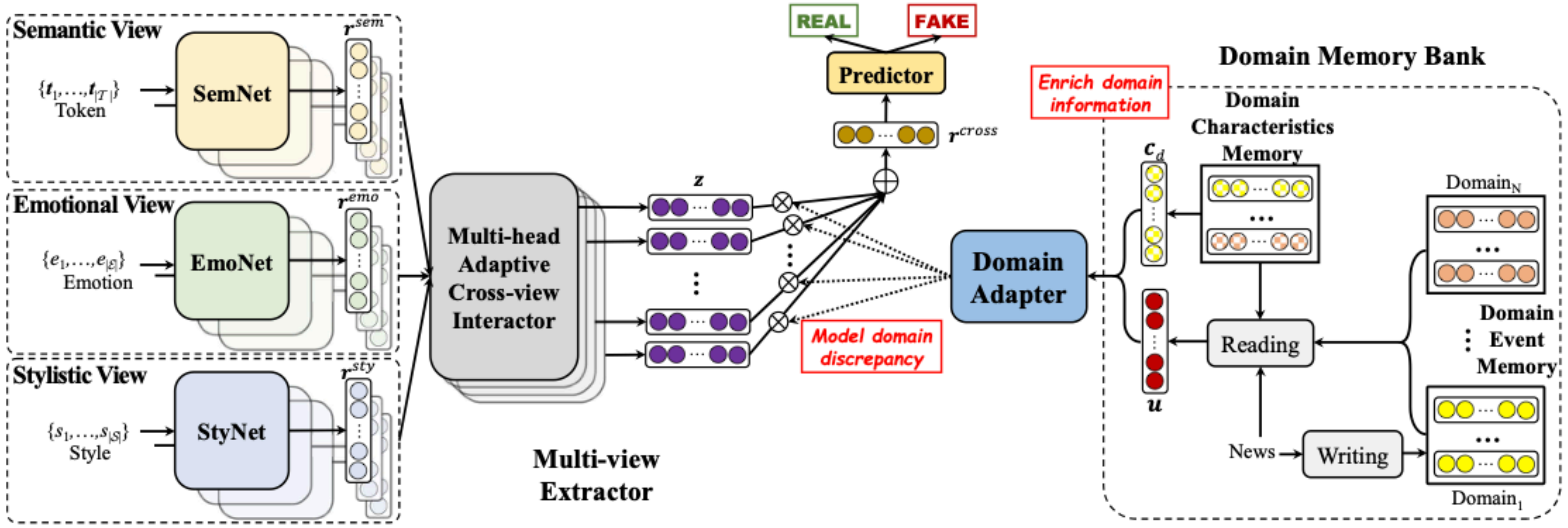


Introduction

MDFEND (CIKM'21)

- Proposed a simple but effective Multi-domain Fake News Detection Model, namely MDFEND.
  - Utilizes a domain gate to aggregate multiple representations extracted by mixture of experts.
- Experiments demonstrate the significant effectiveness improvement of the proposed MDFEND compared with the baselines.





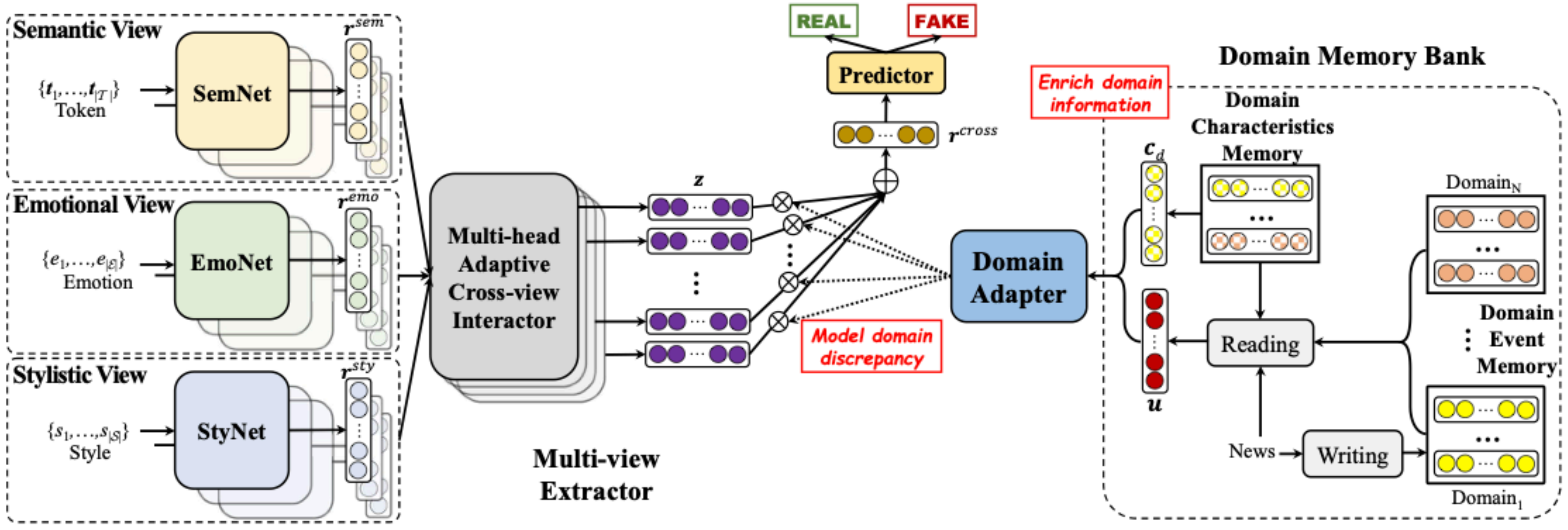
Introduction

M3FEND

- Propose a novel Memory-guided Multi-view Multi-domain FND Framework.
  - Since the distributions of word usage, style, and emotion vary from domain to domain.
    - Propose three multi-channel networks to model news pieces from semantic, emotional, stylistic view, named SemNet, EmoNet, and StyNet.
  - Cross-view interactions could capture associations among different views which benefits modeling the domain discrepancy.
    - Propose a Multi-head Adaptive Cross-view Interactor to adaptively learn various cross-view interactions.

Introduction

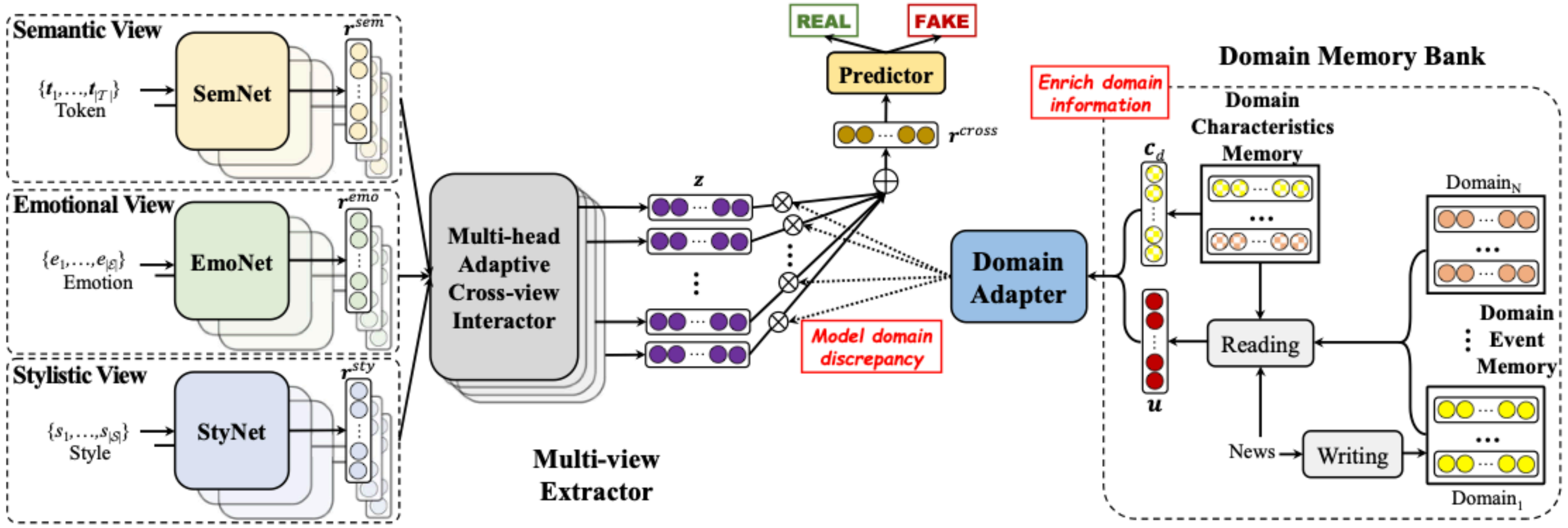
M3FEND



- Propose a novel Memory-guided Multi-view Multi-domain FND Framework.
  - The discriminability of views varies from domain to domain.
    - E.g, the style view is discriminative for science domain while not for entertainment domain.
    - Propose a Domain Adapter with domain information as input to adaptively aggregate discriminative cross-view representations for news in different domains.

Introduction

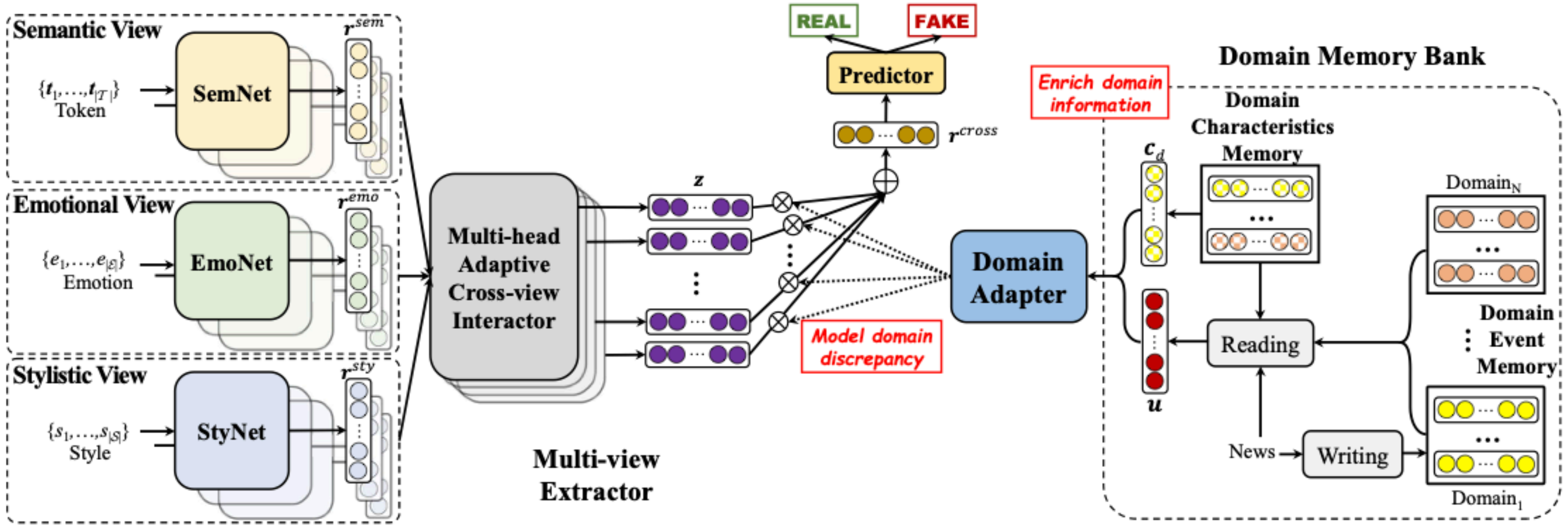
M3FEND



- Propose a novel Memory-guided Multi-view Multi-domain FND Framework.
  - To complete domain labels and enrich domain information.
    - Propose a Domain Memory Bank which consists of a Domain Characteristics Memory and multiple Domain Event Memories.
    - Domain Characteristics Memory aims to automatically capture and store information of domain characteristics.
    - Each domain has a Domain Event Memory matrix which records all news released in this domain.

Introduction

M3FEND



- Propose a novel Memory-guided Multi-view Multi-domain FND Framework.
  - To complete domain labels and enrich domain information.
    - Each Domain Event Memory matrix consists of several memory units, and each unit represents a cluster of similar news.
    - Then compute the similarity between each Domain Event Memory matrix and a certain news piece, it can denote the distribution of domain labels, then utilize it to enrich domain information for news pieces.
    - The enriched domain information is utilized to guide the Domain Adapter to aggregate cross-view representations.

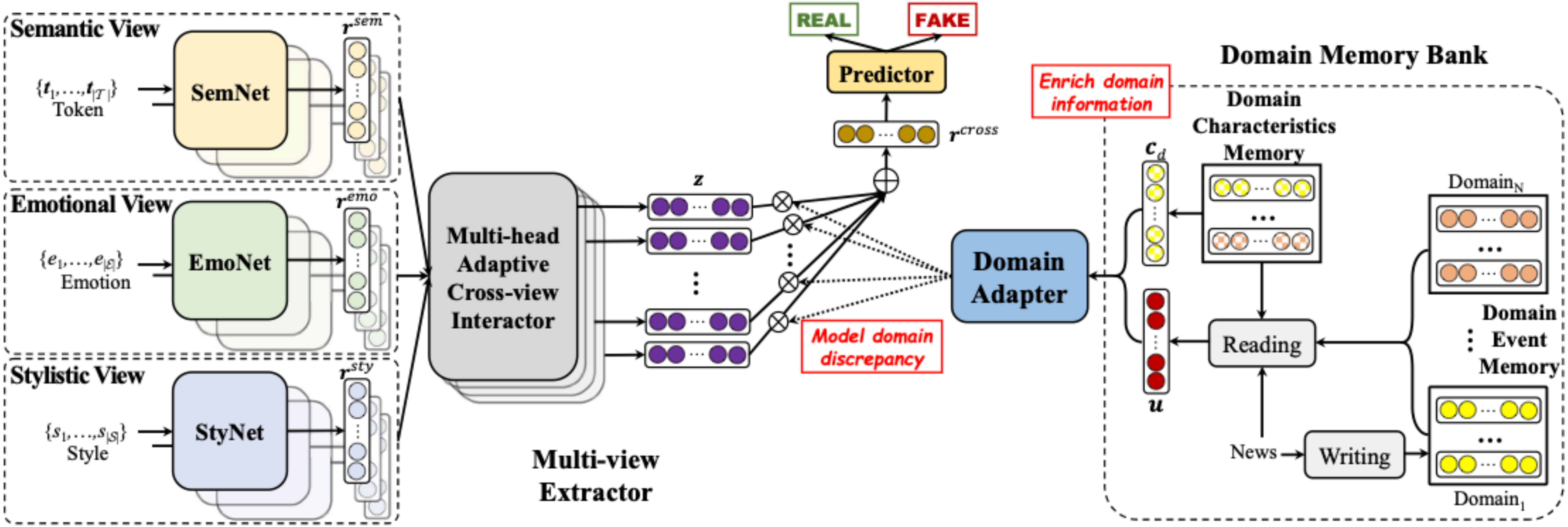
Introduction

Contributions

- Investigate the problem of multi-domain fake news detection and point out two challenges.
  - Domain shift
  - Domain labeling incompleteness
- To solve the challenges, authors propose a novel Memory-guided Multi-view Multi-domain Fake News Detection Framework (M3FEND).
  - Improved the detection performance of most domains.
- Conduct both offline and online experiments to demonstrate the effectiveness of M3FEND.

Methodology

Memory-Guided Multi-View Multi-Domain Fake News Detection (M3FEND)



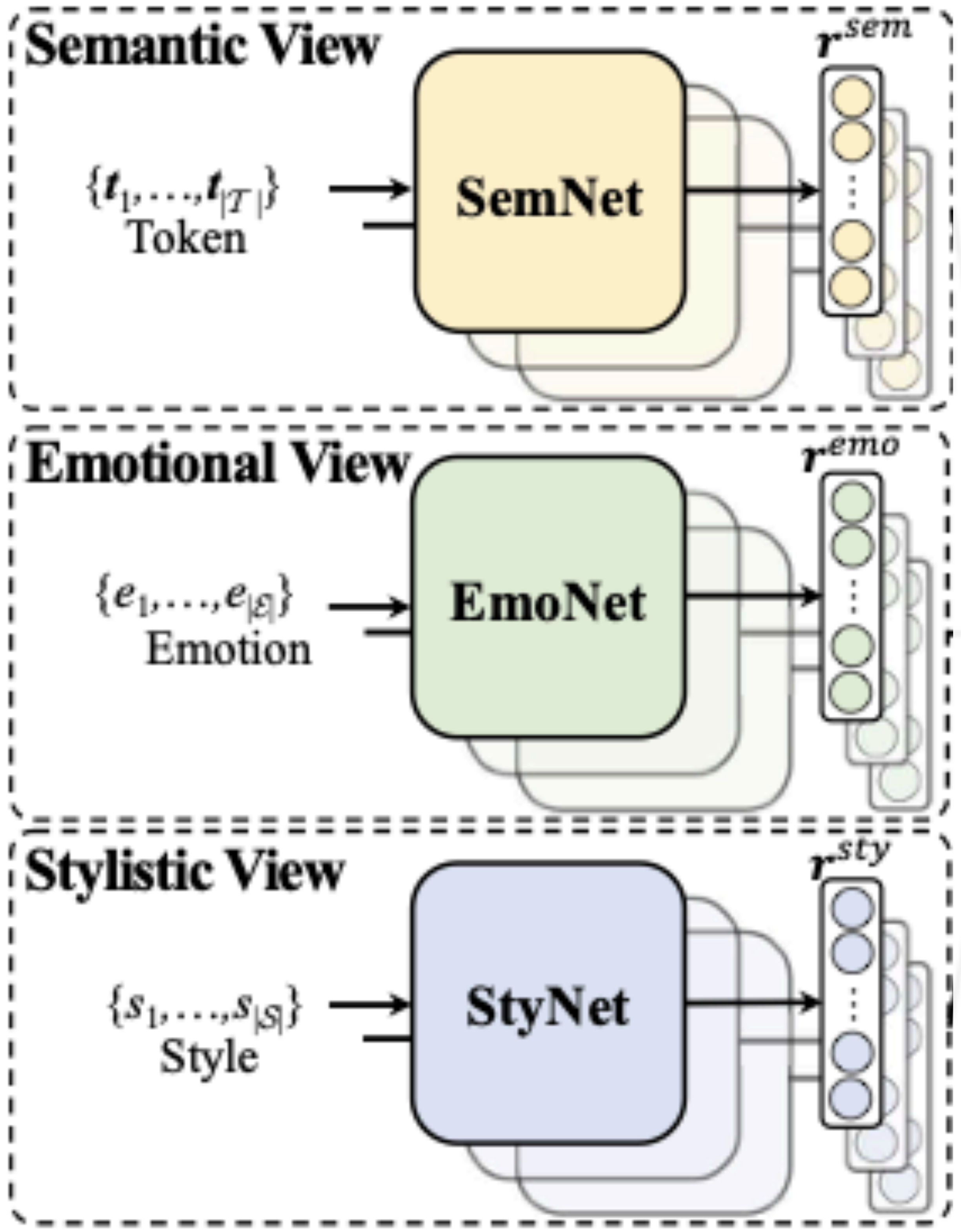
Methodology

Problem Definition

- Let P be a news piece on social media, and the text of the news piece consists of T tokens (words).
- Adopt RoBERTa to encode tokens of the news content as $\mathcal{T} = \{\boldsymbol{t}_1, \ldots, \boldsymbol{t}_{|\mathcal{T}|}\}$.
  - $\boldsymbol{t} \in \mathbb{R}^O$ denotes an embedding, O indicates the dimension of embeddings
- $\mathcal{E} = \{e_1, \ldots, e_{|\mathcal{E}|}\}$: Extract emotion features from the news piece, including emotion category, emotional intensity, sentiment score, and so on.
- $\mathcal{S} = \{s_1, \ldots, s_{|\mathcal{S}|}\}$: Similarly, extract the writing style features of the news piece.
- Ground truth label $y \in \{0,1\}$: real, fake, Domain label $d \in \{Domain_1, \ldots, Domain_N\}$
- Given a P and a d, multi-domain FND aims to detect whether P is fake or real.

Methodology

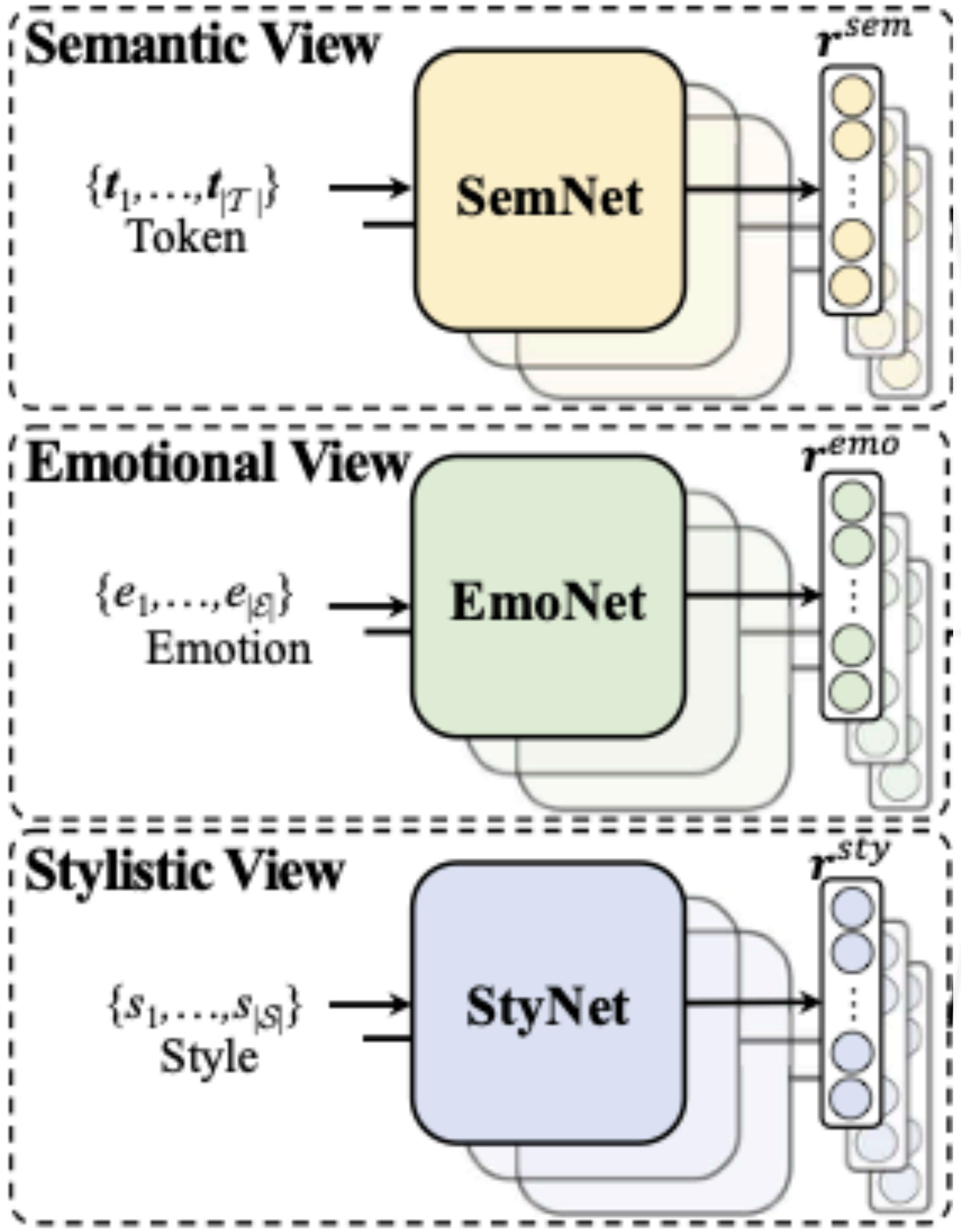
Multi-view Extractor



- Semantic Network (SemNet): $\boldsymbol{r}^{sem} = \mathrm{SemNet}(\{\boldsymbol{t}_1, \ldots, \boldsymbol{t}_{|\mathcal{T}|}\})$
  - It aims to extract representations from the semantic view with the text content of news pieces. (TextCNN)
- Emotion Network (EmoNet): $\boldsymbol{r}^{emo} = \mathrm{EmoNet}(\{e_1, \ldots, e_{|\mathcal{E}|}\})$
  - This part focuses on modeling the emotional view with emotional signals. (MLP)
- Style Network (StyNet): $\boldsymbol{r}^{sty} = \mathrm{StyNet}(\{s_1, \ldots, s_{|\mathcal{S}|}\})$
  - It pays attention to the stylistic view with writing style features. (MLP)

Methodology

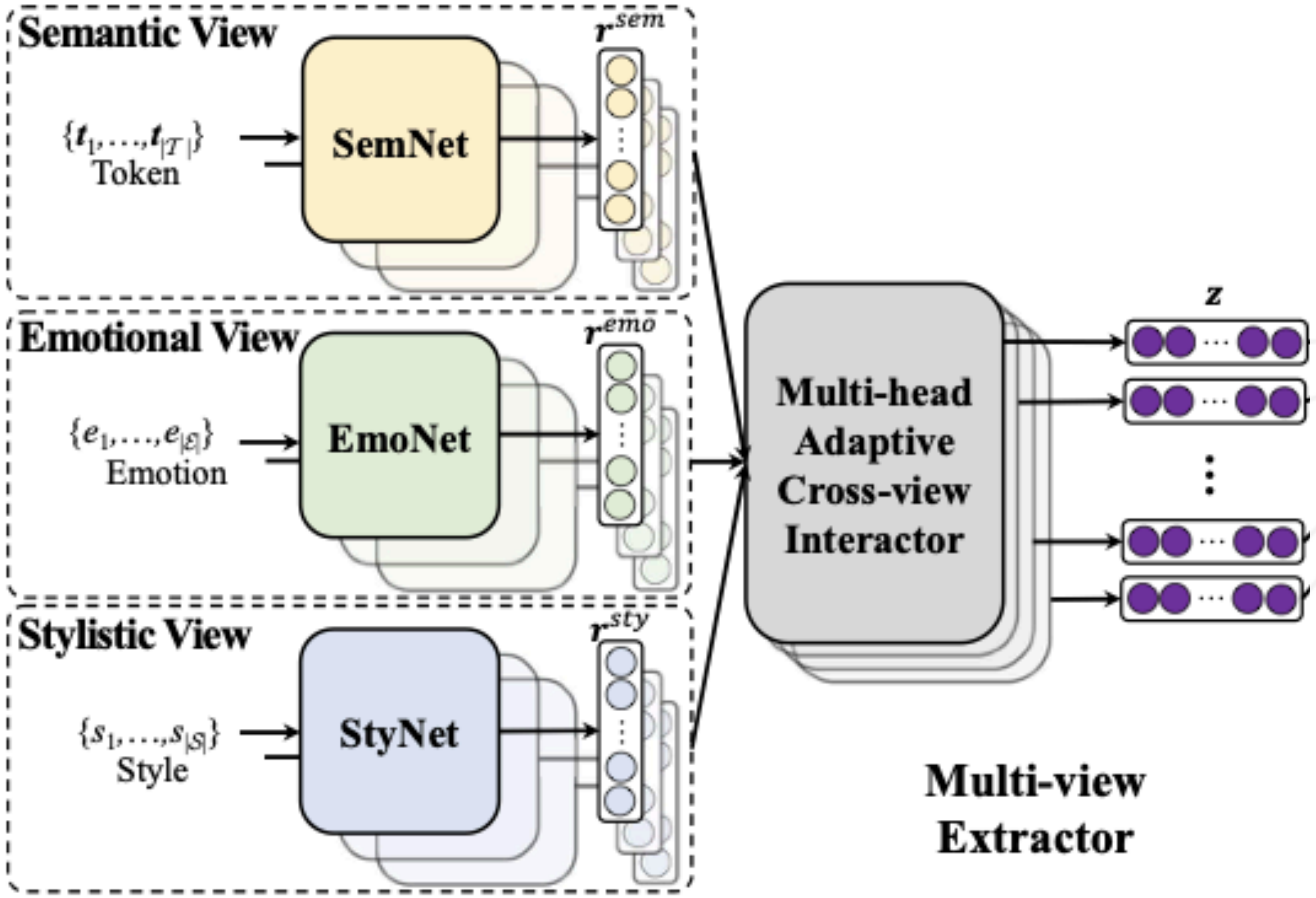
Multi-view Extractor



- Inspired by multi-channel CNN
- Multi-channel extractor allow the model to jointly attend to information from different representation subspace, and different representations could focus on various patterns.
- Then obtain three groups of representations
  - $\{\boldsymbol{r}_i^{sem}\}_{i=1}^{k_{sem}}$, $\{\boldsymbol{r}_i^{emo}\}_{i=1}^{k_{emo}}$, and $\{\boldsymbol{r}_i^{sty}\}_{i=1}^{k_{sty}}$
  - SemNet, EmoNet, StyNet

Methodology

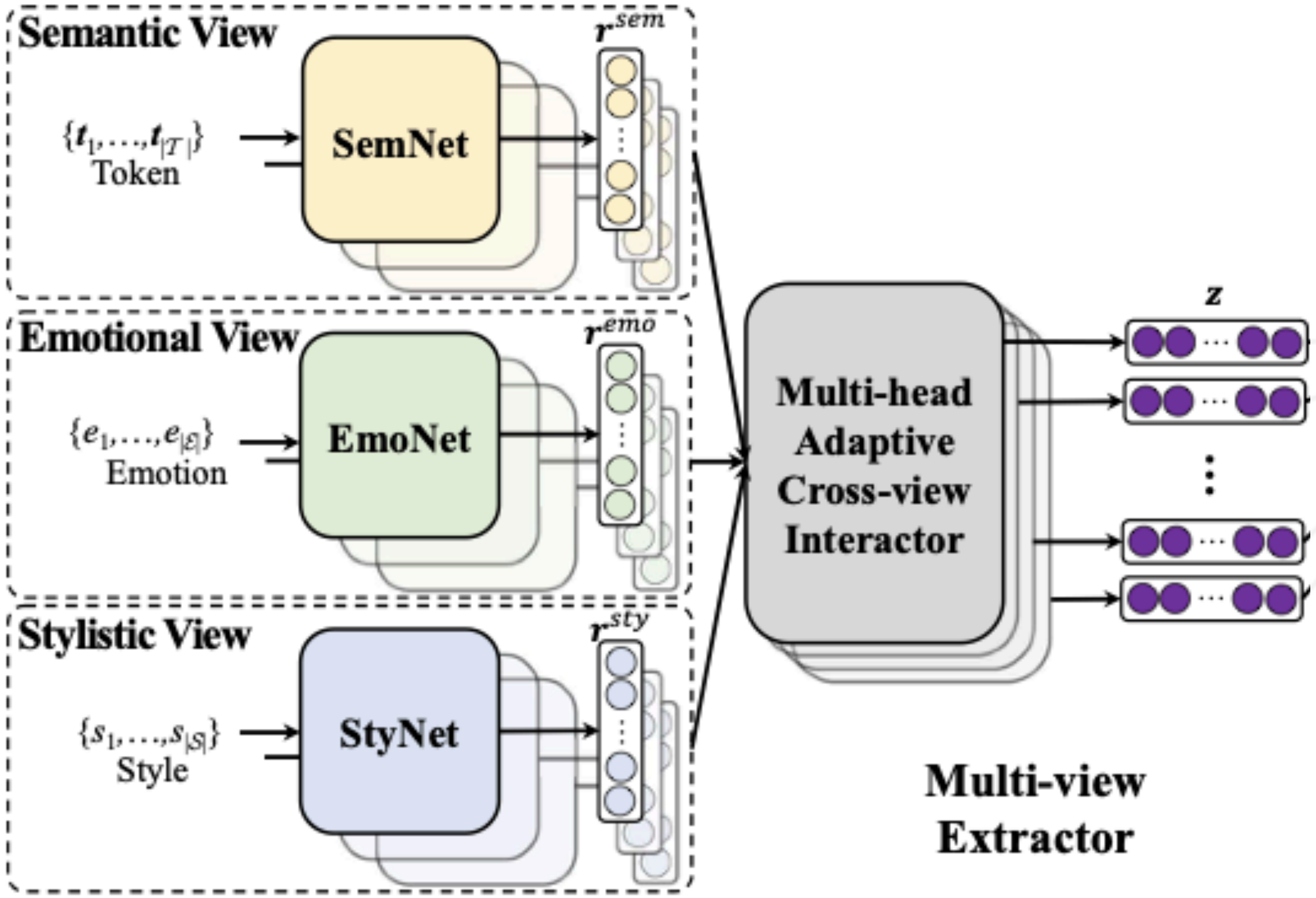
Multi-head Adaptive Cross-view Interactor



- Cross-view interactions could capture associations among different views and produce more diverse combinations of views.
- Propose an Adaptive Cross-view Interactor to automatically learn cross-view representations.
- $$z = \exp\left[\sum_{i=1}^{k_{sem}} a_i^{sem} \ln \boldsymbol{r}_i^{sem} + \sum_{j=1}^{k_{emo}} a_j^{emo} \ln \boldsymbol{r}_j^{emo} + \sum_{q=1}^{k_{sty}} a_q^{sty} \ln \boldsymbol{r}_q^{sty}\right]$$
- $$z = \prod_{i=1}^{k_{sem}} (\boldsymbol{r}_i^{sem})^{a_i^{sem}} \odot \prod_{j=1}^{k_{emo}} (\boldsymbol{r}_j^{emo})^{a_j^{emo}} \odot \prod_{q=1}^{k_{sty}} (\boldsymbol{r}_q^{sty})^{a_q^{sty}}$$

Methodology

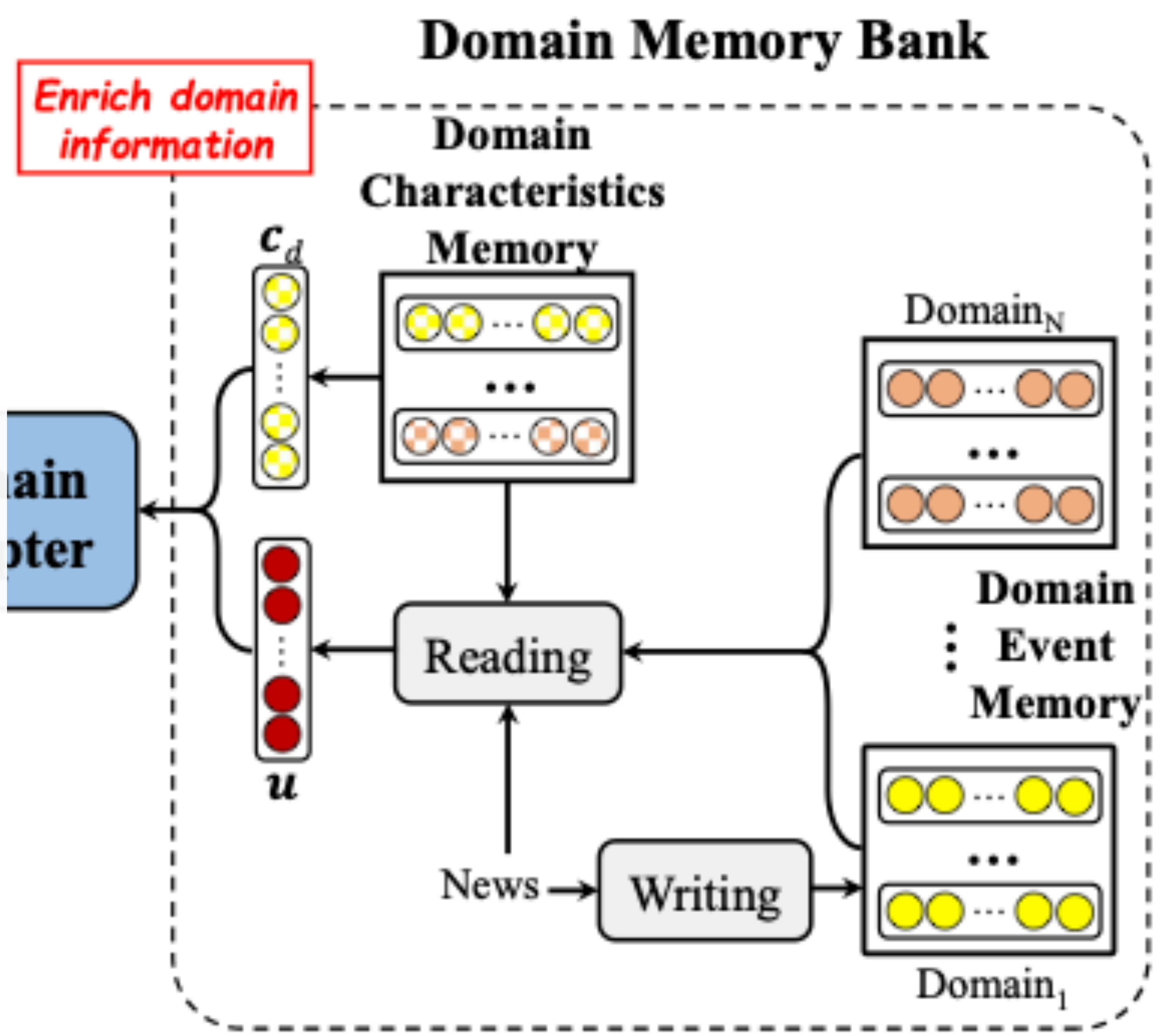
Multi-head Adaptive Cross-view Interactor



- An Adaptive Cross-view Interactor can extract representations of a cross-view interaction.
- However, a single cross-view representation is not discriminative for all domains, thus it's necessary to extract various cross-view representations.
- Along this line, to model different cross-view interactions, propose a Multi-head Adaptive Cross-view Interactor with H heads, and each head adaptively learns a kind of cross-view representation. $\{z_i\}_{i=1}^{H}$

Methodology
Domain Memory Bank

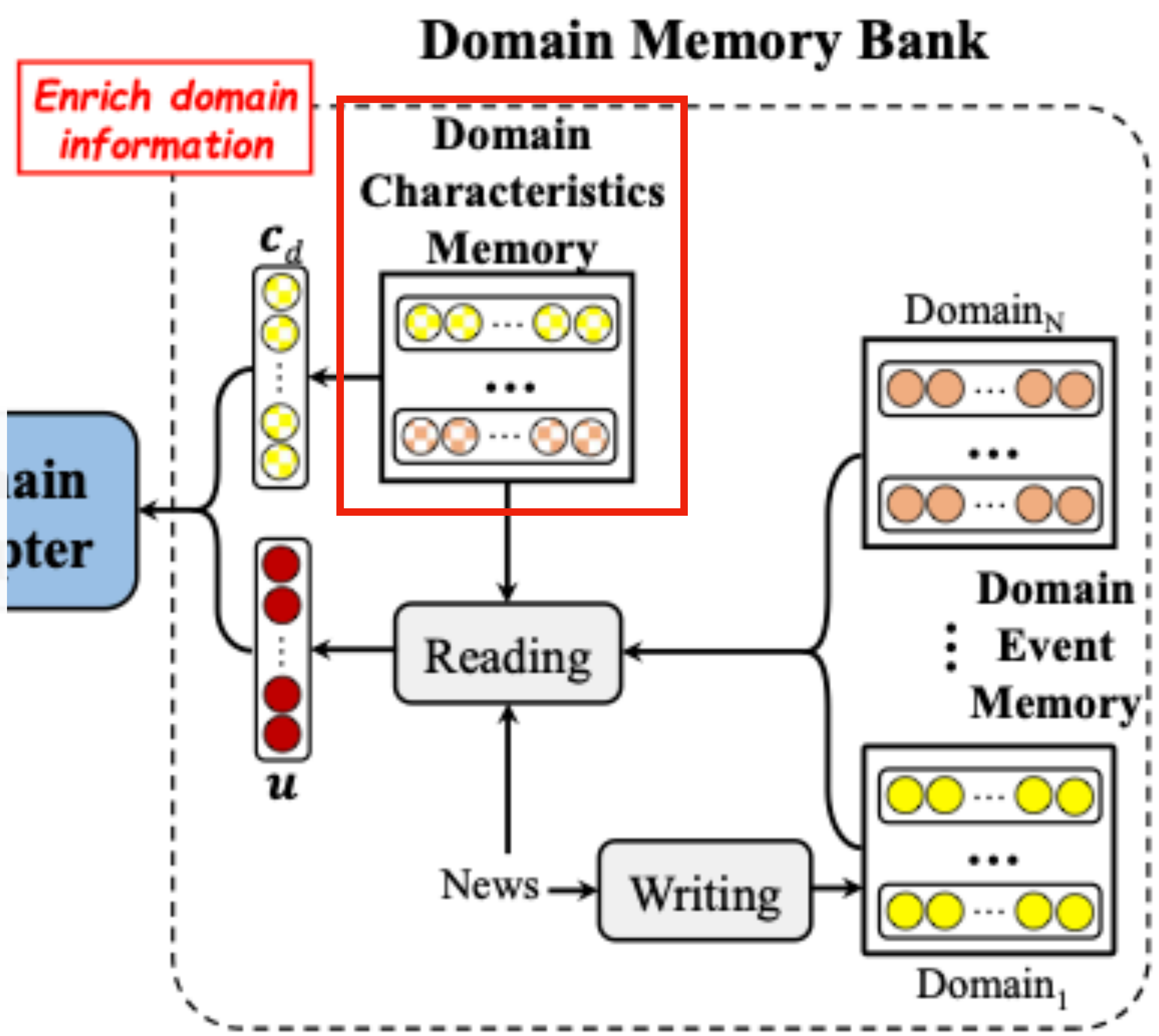
- Domain Memory Bank aims to
  - Complete domain labels
  - Enrich domain information in news pieces
- It consists of
  - A Domain Characteristics Memory
  - A set of Domain Event Memories
- The enrich domain information is utilized as the input of the Domain Adapter.



Methodology

Domain Characteristics Memory

- It aims to automatically capture and store domain characteristics.
- $\mathscr{C} = \{\boldsymbol{c}_i\}_{i=1}^{N}$, $\boldsymbol{c}_i$: a memory unit of i-th domain
- All parameters of the $\mathscr{C}$ are randomly initialized.
- $\boldsymbol{c}_i$ is only learned from training samples of the i-th domain, so it could be seen as the characteristics representation of the i-th domain.

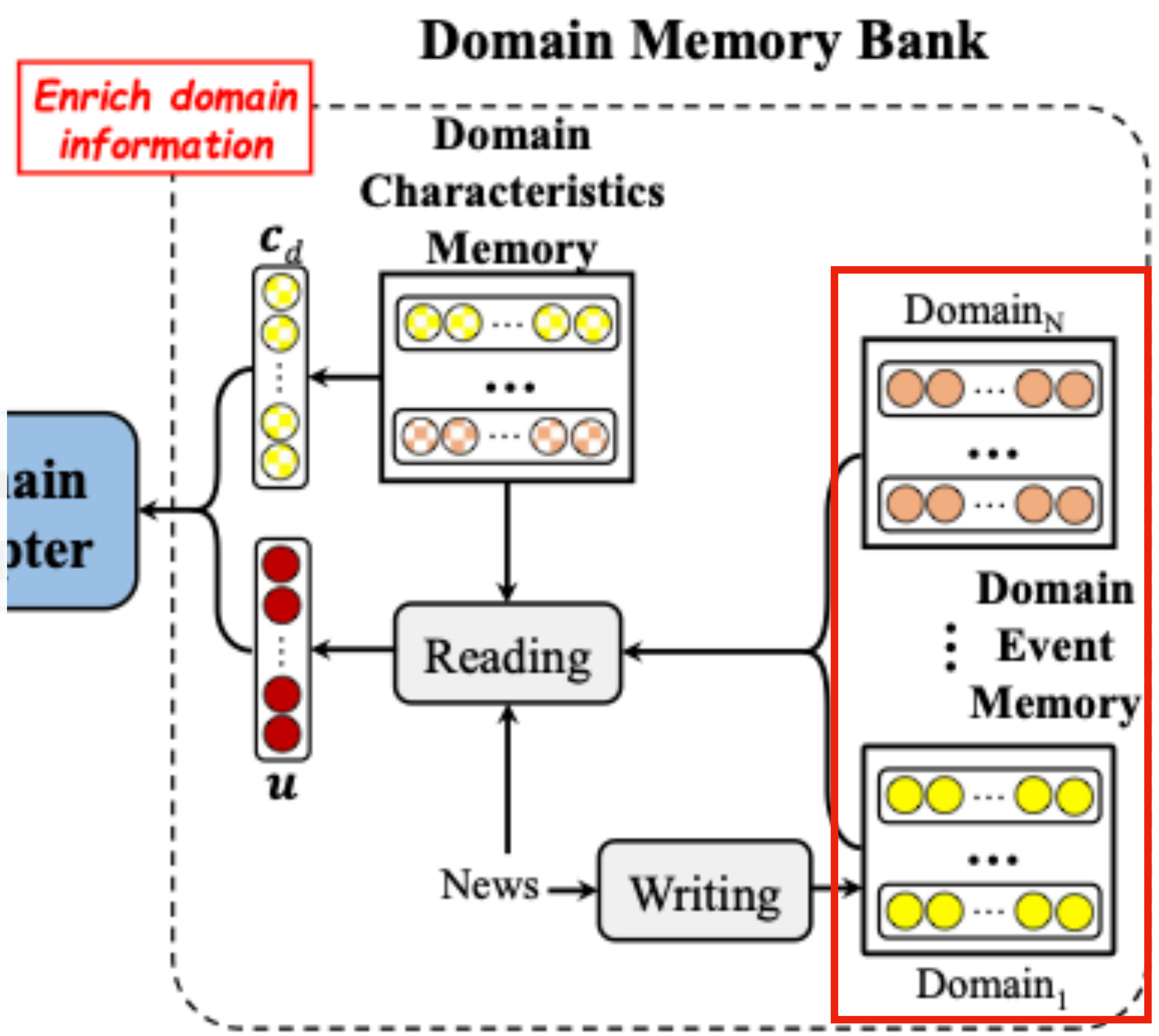


Target News		Trump nearly fainted during his speech and cancelled his subsequent trip. A symptom of COVID-19?
Domain	Similarity v	Representative Example
Science	0.02	NASA used the Nuclear Spectroscopy Telescope to photo the spiral galaxy 1068 in the Cetus.
Military	0.04	U.S. sends 35 medical ships.
Edu.	0.01	A student admitted to Harvard University.
Disaster	0.02	The US "World Journal" reported a five-level fire in a restaurant.
Politics	0.33	US deaths from COVID-19 exceed 100k.
Health	0.21	The animal experiment of Oxford's COVID-19 vaccine failed.
Finance	0.12	Pfizer's stocking price rose 15%, boosted by the company's COVID-19 vaccine news.
Ent.	0.09	10 more people tested positive for COVID-19 in Italian Serie A.
Society	0.16	A COVID-19 carrier refused security check at the airport.

Methodology

Domain Event Memory

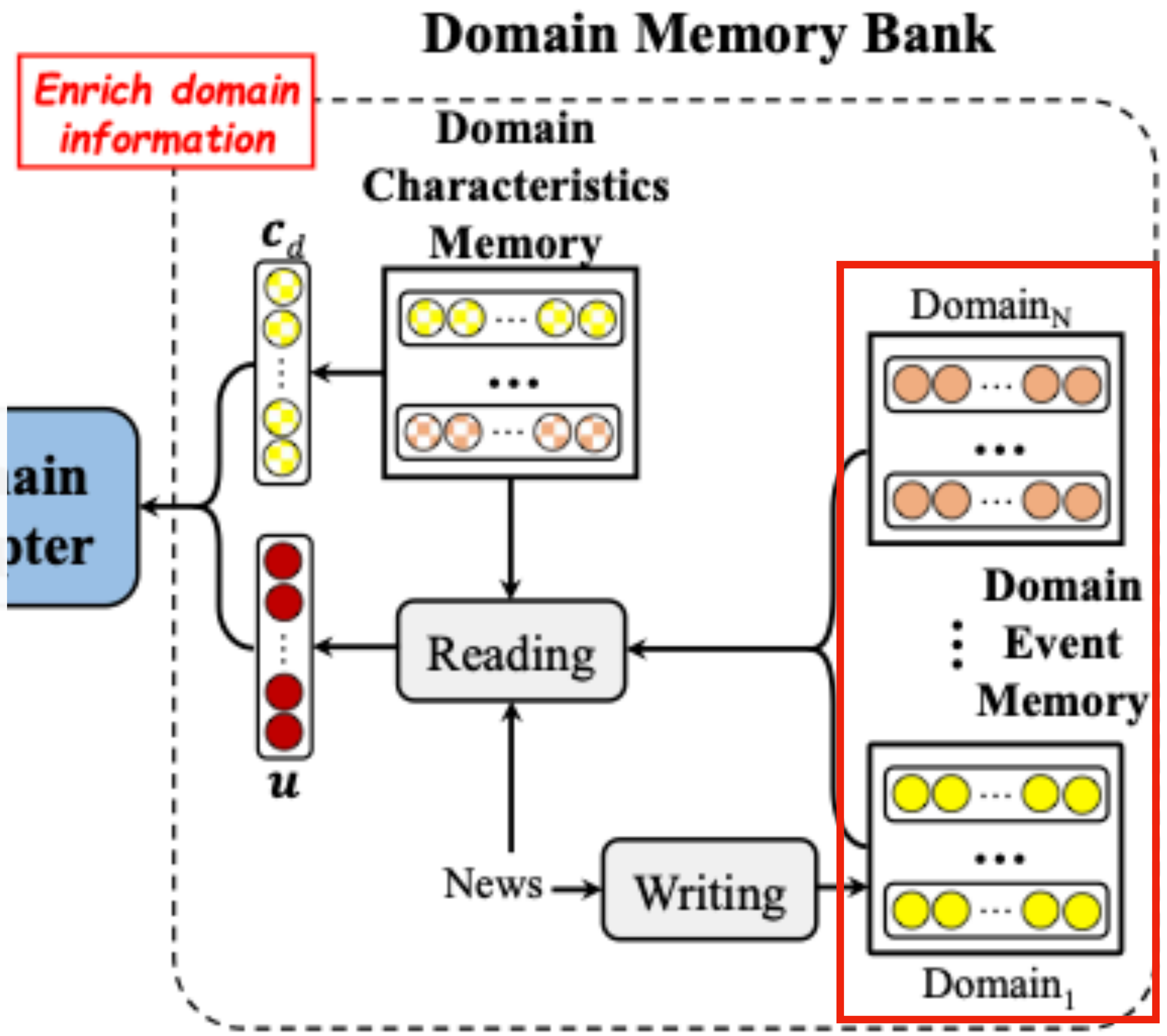
- A news piece is given a specific domain label d, but it may simultaneously contain information of other domains.
- Propose a Domain Event Memory mechanism.
  - To discover potential domain labels of news and enrich domain information.
  - Domain Event Memory matrix records all news released in this domain, and for a news piece, evaluate the similarity between the news and all Domain Event Memory matrices.
    - The similarity can represent the distributions of potential domain labels.



Methodology

Domain Event Memory

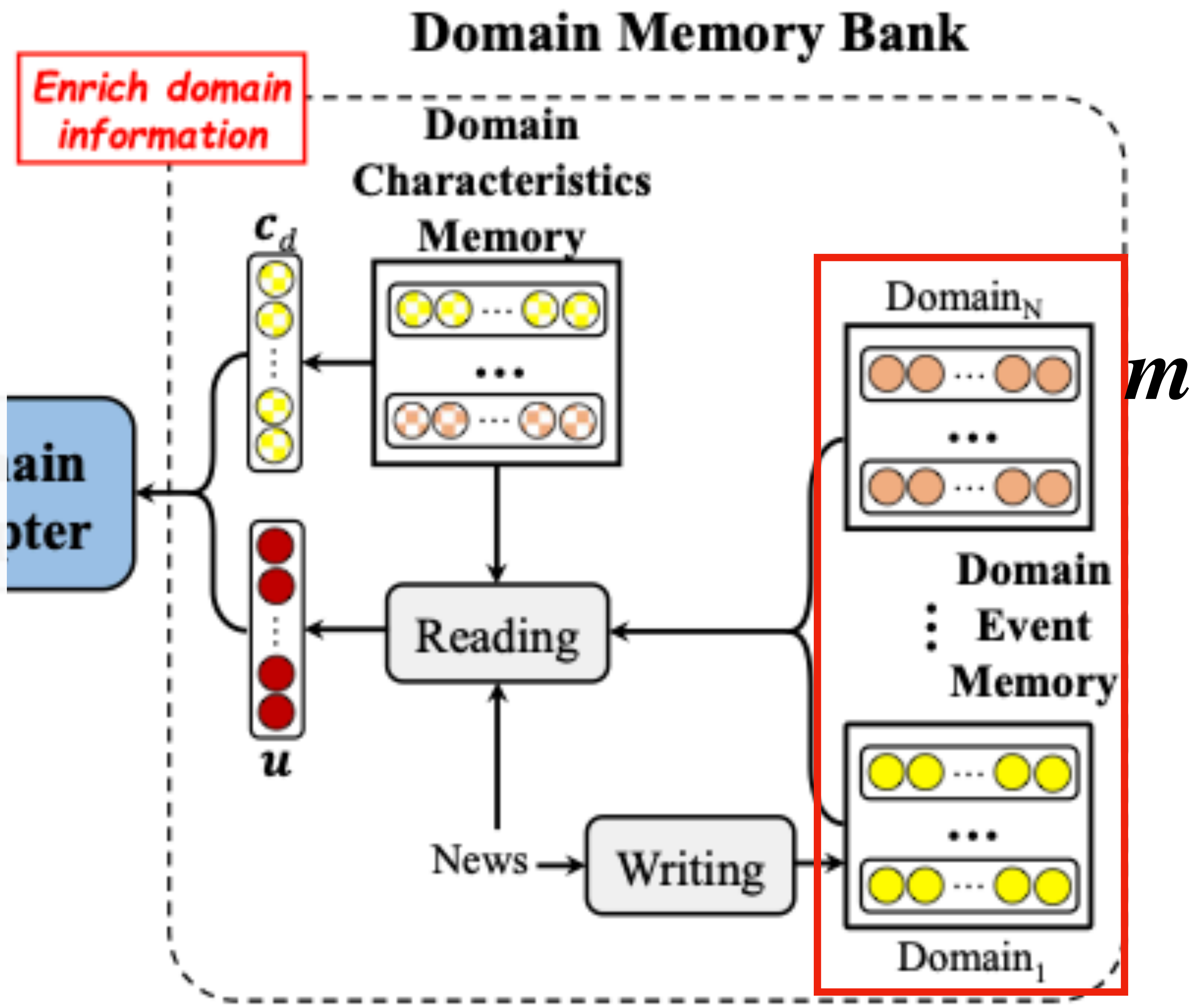
- Domain Event Memory of the j-th domain
- $\mathscr{M}_j = \{\boldsymbol{m}_i\}_{i=1}^{Q}$, $\boldsymbol{m}_i$: memory unit of cluster i
- A memory unit $\boldsymbol{m}$ represents a set of similar news pieces, and all news pieces in a specific news domain can be divided into Q clusters.
- Each domain has a Domain Event Memory matrix, so there are N Domain Event Memory matrices.



Methodology

Domain Event Memory – Initialization

- Aggregate news representations into Q clusters using K-means for each domain, respectively.
- For a specific domain, all centers of clusters are utilized to initialize its memory units $\boldsymbol{m}$.



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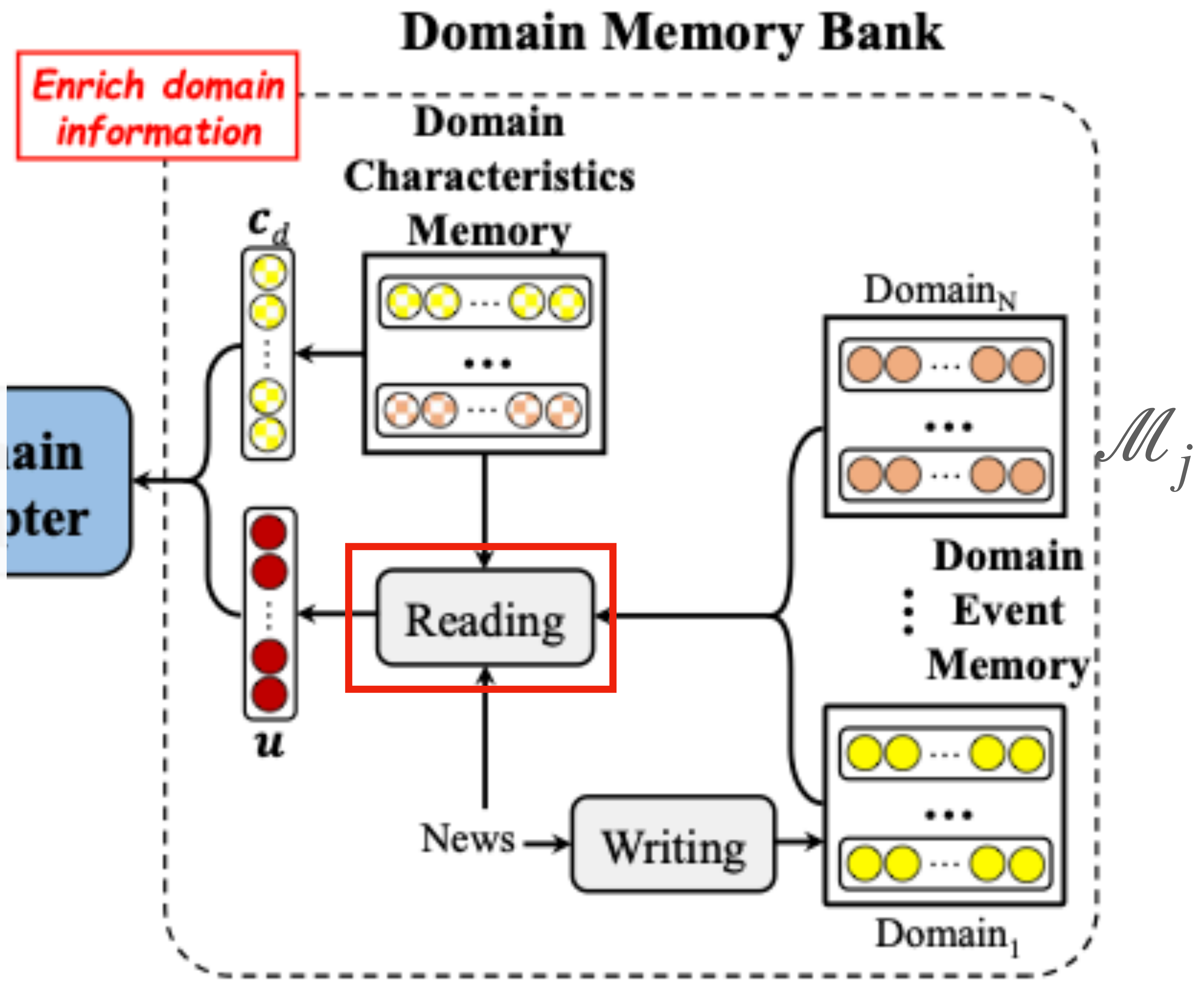
Methodology

Domain Event Memory – Reading

- This operation aims to evaluate the similarity between a news piece and all Domain Event Memory matrices.
- Domain representation
  - $\boldsymbol{o}_j = \mathrm{softmax}(\boldsymbol{n} W g(\mathscr{M}_j)/\tau)\mathscr{M}_j$
  - $\mathscr{D} = [\boldsymbol{o}_1, \ldots, \boldsymbol{o}_N]$
- Similarity distribution: $\boldsymbol{v} = \mathrm{softmax}(\boldsymbol{n} V g(\mathscr{D}))$
- $\boldsymbol{n}$: representation of news piece, $g(\cdot)$: transpose function, W, V: learnable parameter matrix



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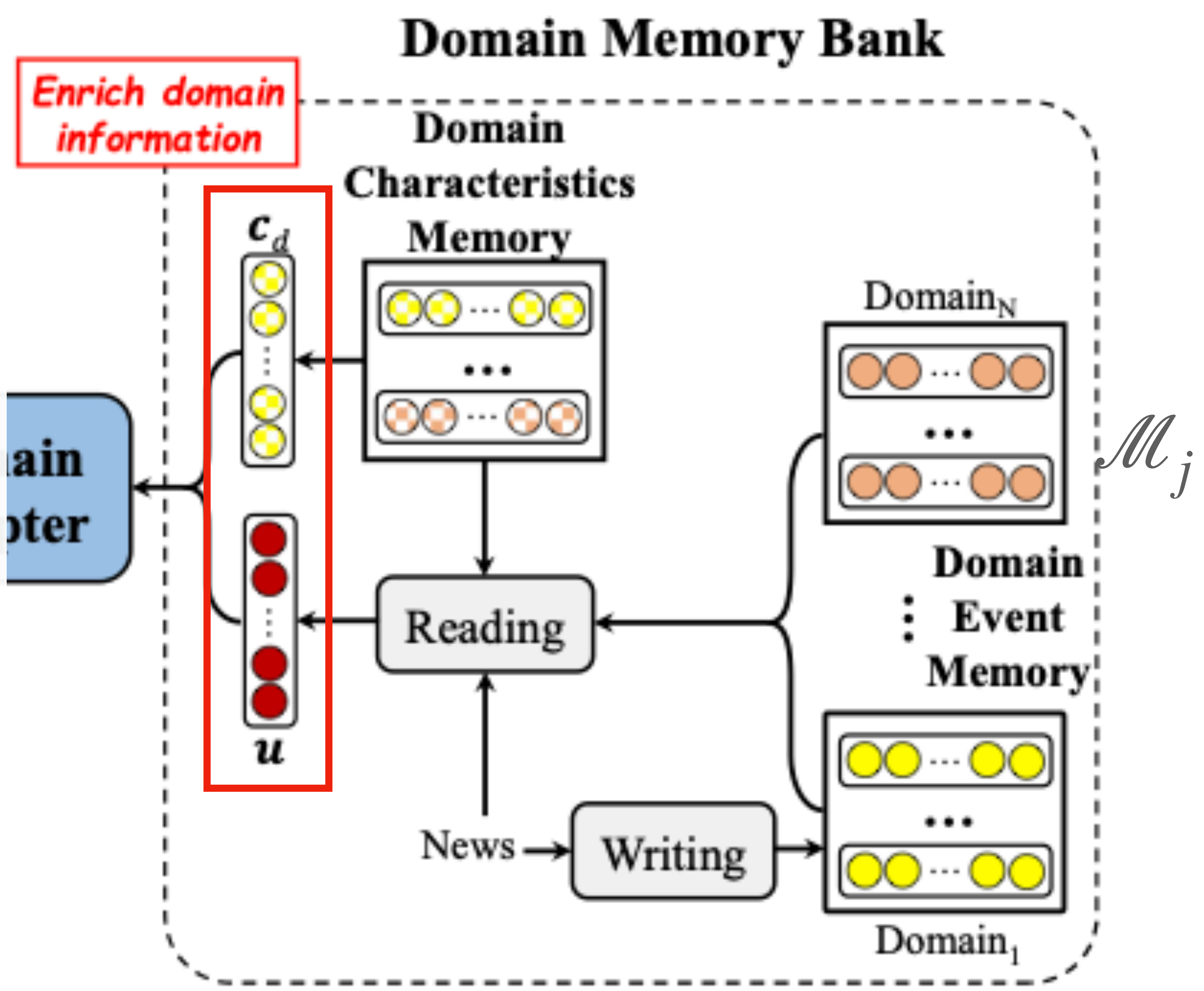
Methodology

Domain Event Memory – Reading

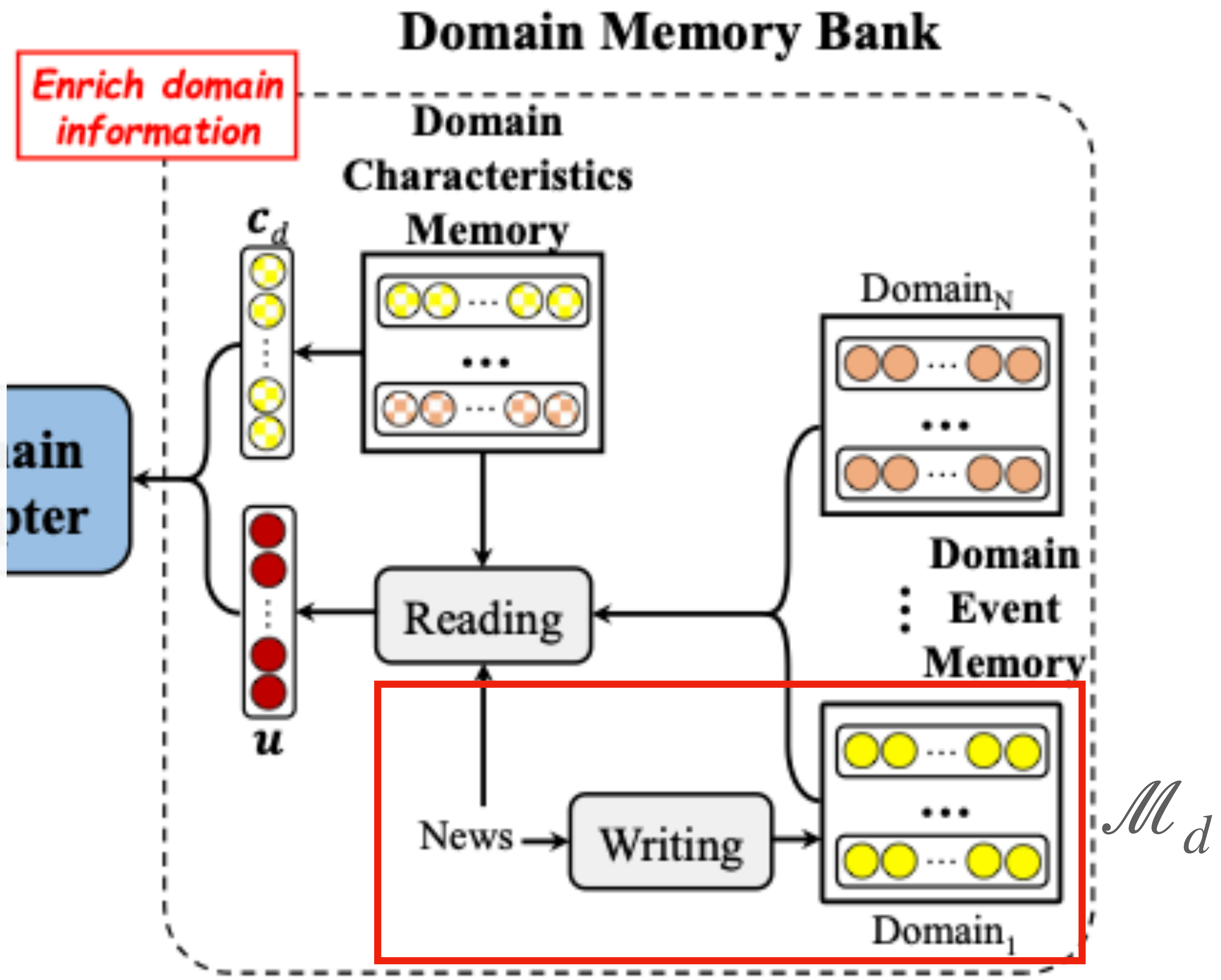
- For a news piece with domain label d, look up the Domain Characteristics Memory $\mathscr{C}$ to obtain an explicit domain representation c_d.
- Then evaluate an implicit domain representation as $\boldsymbol{u} = \sum_{i=1}^{N} v_i \boldsymbol{c}_i$.
- Finally, the implicit representation $\boldsymbol{u}$ and the explicit representation c_d are concentrated into $[c_d, \boldsymbol{u}]$.
  - To represent enriched domain information in the news piece.



Methodology

Domain Event Memory - Writing

- A given domain label d indicates that the news piece contains topics of a certain domain.
- Inspired by Neural Turing machine (NTM).
- Thus, store the news piece in the specific Domain Event Memory $\mathscr{M}_d$.
  - $\boldsymbol{sim} = \mathrm{softmax}(\boldsymbol{n}Wg(\mathscr{M}_d)/\tau)$
  - $\boldsymbol{erase}_i = \boldsymbol{sim}_i \cdot \boldsymbol{m}_i$, $\boldsymbol{add}_i = \boldsymbol{sim}_i \cdot \boldsymbol{n}$
  - $\boldsymbol{m}_i = \boldsymbol{m}_i - \beta \boldsymbol{erase}_i + \beta \boldsymbol{add}_i$



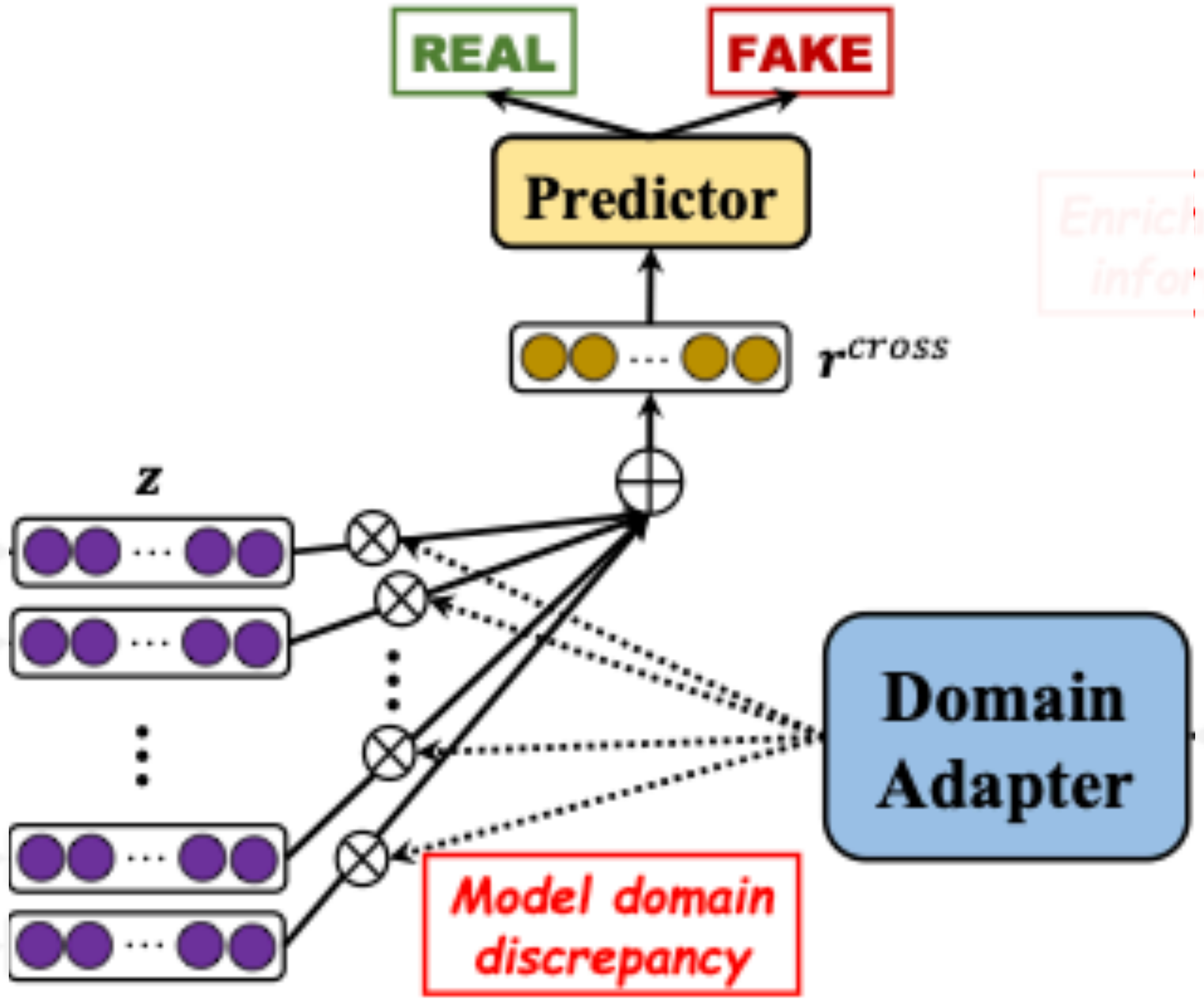
Methodology

Domain Adapter

- Propose a Domain Adapter to model the domain discrepancy.

- The Domain Adapter takes the enriched domain representation $[c_d, \boldsymbol{u}]$ from the Domain Memory Bank as input to aggregate useful cross-view representations for final prediction.

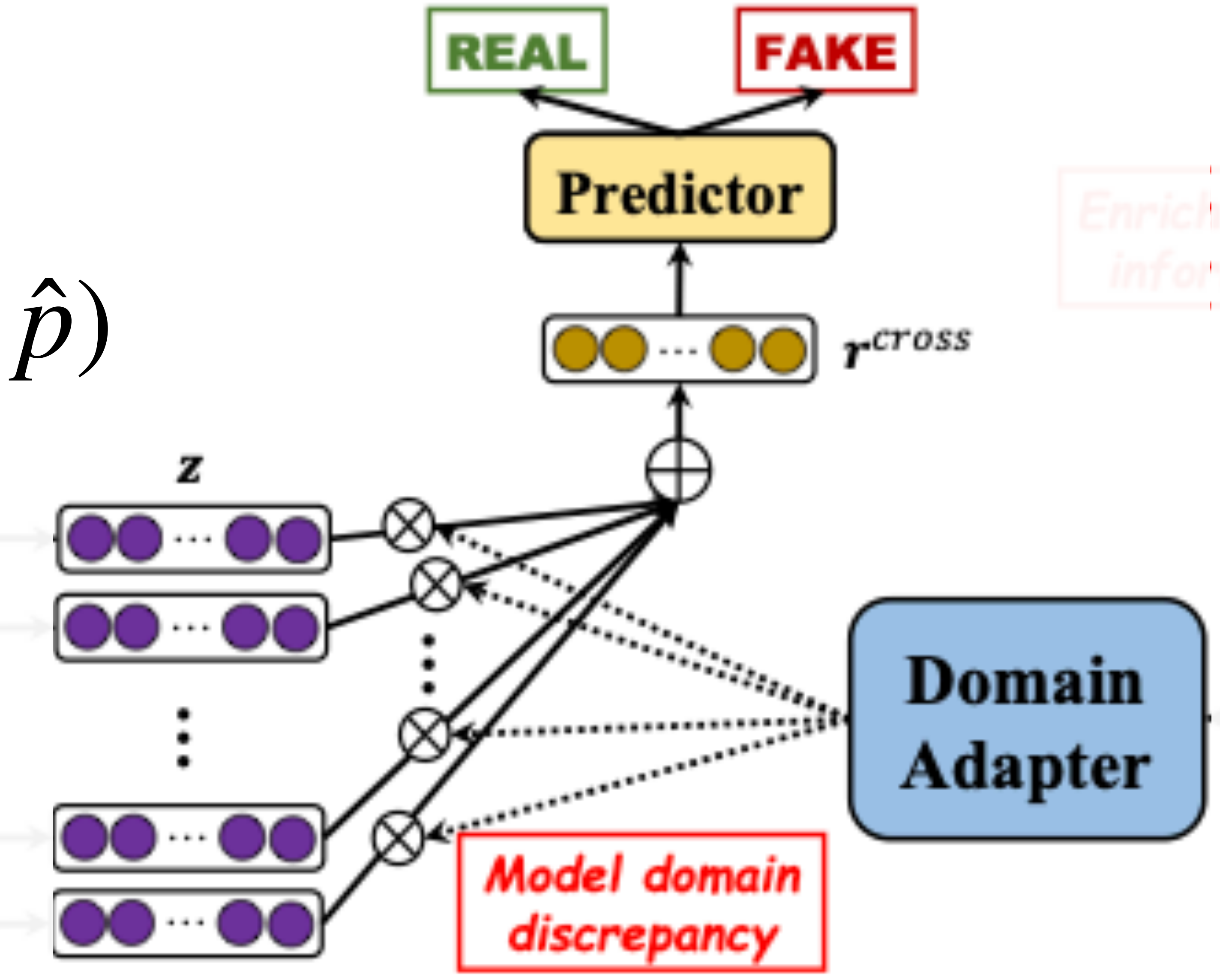
- $\boldsymbol{r} = \sum_{i=1}^{H} w_i z_i, \quad \boldsymbol{w} = \mathrm{softmax}(f[\boldsymbol{c}_d, \boldsymbol{u}]))$



Methodology

Predictor

- $\hat{p} = \text{Sigmoid}(\text{MLP}(\boldsymbol{r}))$
- $\mathscr{L} = -y \log \hat{p} - (1 - y)\log(1 - \hat{p})$



Experiments

Research Questions

- Does proposed M3FEND outperform other approaches in different datasets?
- What are the effects of different views and components in our proposed M3FEND?
- How does M3FEND model the domain discrepancy and find potential domain labels?
- How sensitive are the hyper-parameters?

Experiments

Research Questions

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- How does M3FEND model the domain discrepancy and find potential domain labels?
- How sensitive are the hyper-parameters?

Experiments

Datasets

Domain	Science	Military	Edu.	Disasters	Politics	Health	Finance	Ent.	Society	All
#Real	143	121	243	185	306	485	959	1,000	1,198	4,640
#Fake	93	222	248	591	546	515	362	440	1,471	4,488
Total	236	343	491	776	852	1,000	1,321	1,440	2,669	9,128

domain	Gossipcop	Politifact	COVID	All
#Real	16,804	447	4,750	22,001
#Fake	5,067	379	1,317	6,763
Total	21,871	826	6,067	28,764

- English dataset (En-3)
  - FakeNewsNet (GossipCop, Politifact), COVID
- Chinese dataset (Ch-9)
  - MDFEND (CIKM'21)
  - To testify the effectiveness of M3FEND under various scenarios, sample two datasets as Ch-3 and Ch-6.
  - Ch-3 contains the same three domains as the En-3 dataset. Ch-6 contains 6 domains that are related to daily life, including Education, Disaster, Health, Finance, Entertainment, and Society.

Experiments

Baselines (1/2)

- Single-domain (separately train models for each domain)
  - BiGRU, TextCNN, RoBERTa
- Mixed-domain (combine all domains into a single domain)
  - BiGRU, TextCNN, RoBERTa
  - StyleLSTM[AAAI'20]: feeds the representation and style features into an MLP to obtain the final prediction.
  - DualEmo[WWW'21]: exploits both the representation and emotion features to predict fake or real.

Experiments

Baselines (2/2)

- Multi-domain
  - EANN(KDD'18): It aims to learn event-invariant representations.
  - MMoE(KDD'18): is a popular multi-domain model that shares a mixture-of-experts (MoE) across various domains, and each domain has its specific head.
  - MoSE: is a recent multi-domain model that replaces the experts of MMoE with LSTM.
  - EDDFN(AAAI'21): is a multi-domain fake news detection model which preserves domain-specific and domain-shared knowledge.
  - MDFEND(CIKM'21): is the latest multi-domain fake new detection model which utilizes a Domain Gate to select useful experts of MoE.

Experiments

Offline Result

Results on the Ch-6 dataset. * ($p \leq 0.05$) and ** ($p \leq 0.005$) indicate paired t-test of M^{3}FEND vs. the best baseline.

	Methods	Edu.	Disaster	Health	Finance	Ent.	Society	overall F1	overall Acc	overall AUC
single	BiGRU	0.7697	0.7191	0.8451	0.8247	0.8026	0.8015	0.8266	0.8270	0.8979
single	TextCNN	0.7805	0.4388	0.9012	0.7671	0.7930	0.8654	0.8494	0.8499	0.9195
single	RoBERTa	0.8175	0.7584	0.8909	0.8498	0.8549	0.8304	0.8576	0.8580	0.9288
mixed	BiGRU	0.8253	0.7938	0.8626	0.8254	0.8604	0.8206	0.8491	0.8501	0.9249
mixed	TextCNN	0.8593	0.8240	0.8832	0.8646	0.8659	0.8641	0.8776	0.8783	0.9483
mixed	RoBERTa	0.8664	0.8515	0.9100	0.8700	0.8872	0.8634	0.8872	0.8877	0.9494
mixed	StyleLSTM	0.8565	0.8374	0.9080	0.8766	0.8957	0.8546	0.8844	0.8851	0.9489
mixed	DualEmo	0.8472	0.8352	0.9055	0.8951	0.9043	0.8642	0.8904	0.8909	0.9579
multi	EANN	0.8613	0.8657	0.9150	0.8621	0.8871	0.8791	0.8919	0.8925	0.9605
multi	MMoE	0.8625	0.8777	0.9260	0.8546	0.8882	0.8655	0.8894	0.8900	0.9563
multi	MoSE	0.8569	0.8588	0.9118	0.8639	0.8904	0.8757	0.8913	0.8918	0.9533
multi	EDDFN	0.8780	0.8734	0.9280	0.8456	0.8819	0.8716	0.8917	0.8921	0.9544
multi	MDFEND	0.8826	0.8781	0.9430	0.8749	0.9095	0.8940	0.9093	0.9097	0.9694
	M^{3}FEND	**0.8836**	**0.8824**	**0.9515***	**0.8997***	**0.9296****	**0.9043****	**0.9208****	**0.9211****	**0.9762***

Experiments
Offline Result

Results on the Ch-6 dataset. * ($p \leq 0.05$) and ** ($p \leq 0.005$) indicate paired t-test of M^{3}FEND vs. the best baseline.

	Methods	Edu.	Disaster	Health	Finance	Ent.	Society	overall F1	overall Acc	overall AUC
single	BiGRU	0.7697	0.7191	0.8451	0.8247	0.8026	0.8015	0.8266	0.8270	0.8979
single	TextCNN	0.7805	0.4388	0.9012	0.7671	0.7930	0.8654	0.8494	0.8499	0.9195
single	RoBERTa	0.8175	0.7584	0.8909	0.8498	0.8549	0.8304	0.8576	0.8580	0.9288
mixed	BiGRU	0.8253	0.7938	0.8626	0.8254	0.8604	0.8206	0.8491	0.8501	0.9249
mixed	TextCNN	0.8593	0.8240	0.8832	0.8646	0.8659	0.8641	0.8776	0.8783	0.9483
mixed	RoBERTa	0.8664	0.8515	0.9100	0.8700	0.8872	0.8634	0.8872	0.8877	0.9494
mixed	StyleLSTM	0.8565	0.8374	0.9080	0.8766	0.8957	0.8546	0.8844	0.8851	0.9489
mixed	DualEmo	0.8472	0.8352	0.9055	0.8951	0.9043	0.8642	0.8904	0.8909	0.9579
multi	EANN	0.8613	0.8657	0.9150	0.8621	0.8871	0.8791	0.8919	0.8925	0.9605
multi	MMoE	0.8625	0.8777	0.9260	0.8546	0.8882	0.8655	0.8894	0.8900	0.9563
multi	MoSE	0.8569	0.8588	0.9118	0.8639	0.8904	0.8757	0.8913	0.8918	0.9533
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Experiments

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Experiments

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Experiments

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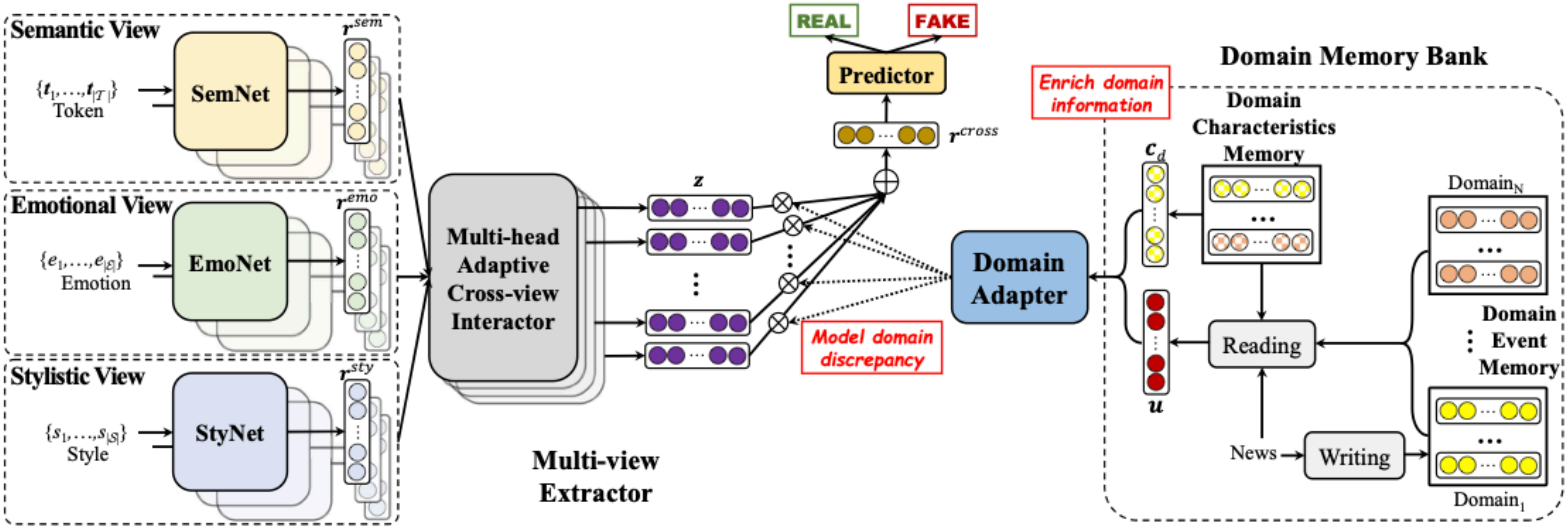
Experiments
Research Questions

- Does proposed M3FEND outperform other approaches in different datasets?
- What are the effects of different views and components in our proposed M3FEND?
- How does M3FEND model the domain discrepancy and find potential domain labels?
- How sensitive are the hyper-parameters?

Experiments

Ablation Study (1/2)

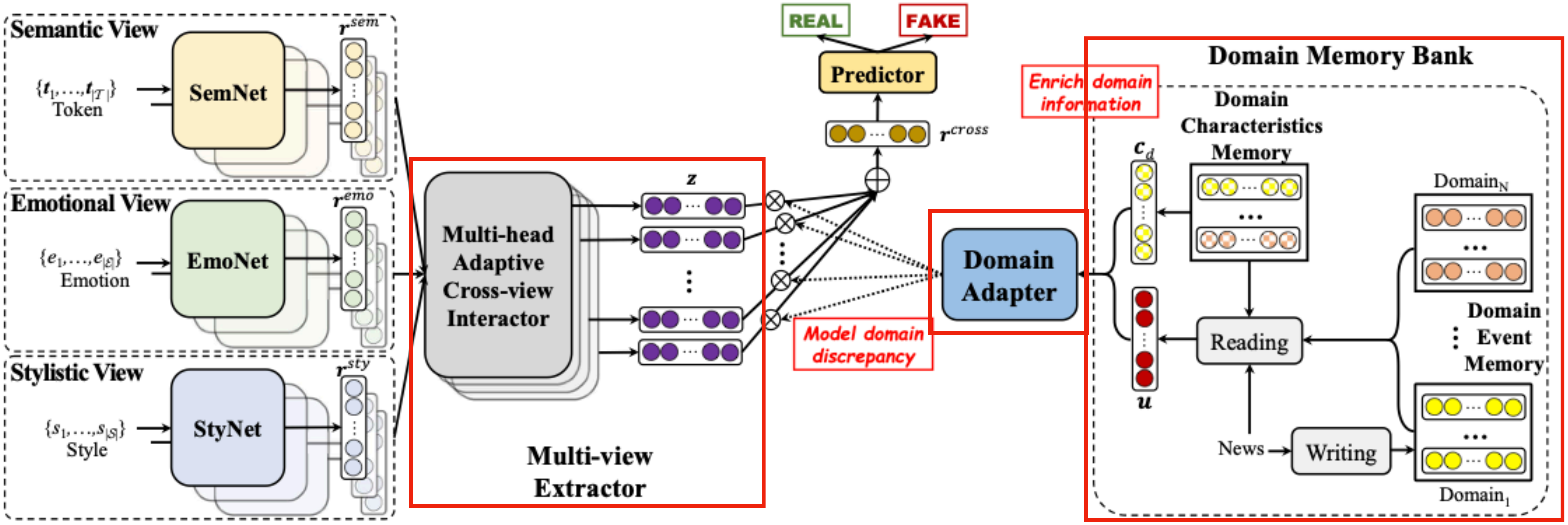
	Ch-3	Ch-6	Ch-9	En-3
M^{3}FEND	**0.9308**	**0.9208**	**0.9216**	**0.8517**
w/o SemView	0.8202	0.8161	0.8249	0.6573
w/o EmoView	0.9195	0.9136	0.9147	0.8403
w/o StyView	0.9255	0.9178	0.9177	0.8472



Experiments

Ablation Study (2/2)

	Ch-3	Ch-6	Ch-9	En-3
M^{3}FEND	**0.9308**	**0.9208**	**0.9216**	**0.8517**
w/o Interactor	0.9217	0.9169	0.9173	0.8398
w/o Memory	0.9237	0.9182	0.9176	0.8501
w/o Adapter	0.9172	0.9169	0.9157	0.8367



Experiments
Research Questions

- Does proposed M3FEND outperform other approaches in different datasets?
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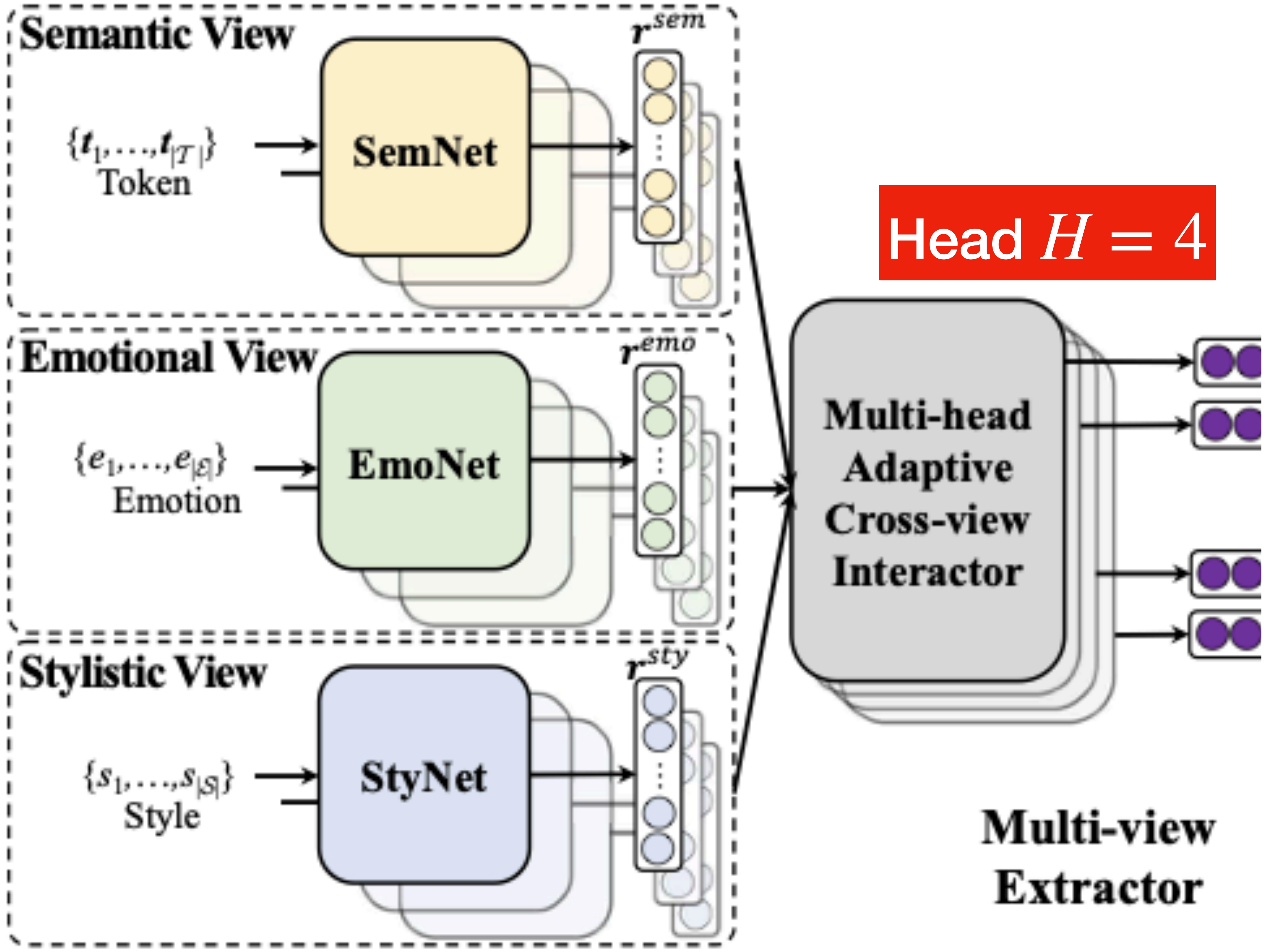
Experiments

Effectiveness of Domain Discrepancy Modeling

Channel number $k = 1$

Head $H = 4$



$$z = \prod_{i=1}^{k_{sem}} (r_i^{sem})^{a_i^{sem}} \odot \prod_{j=1}^{k_{emo}} (r_j^{emo})^{a_j^{emo}} \odot \prod_{q=1}^{k_{sty}} (r_q^{sty})^{a_q^{sty}}$$

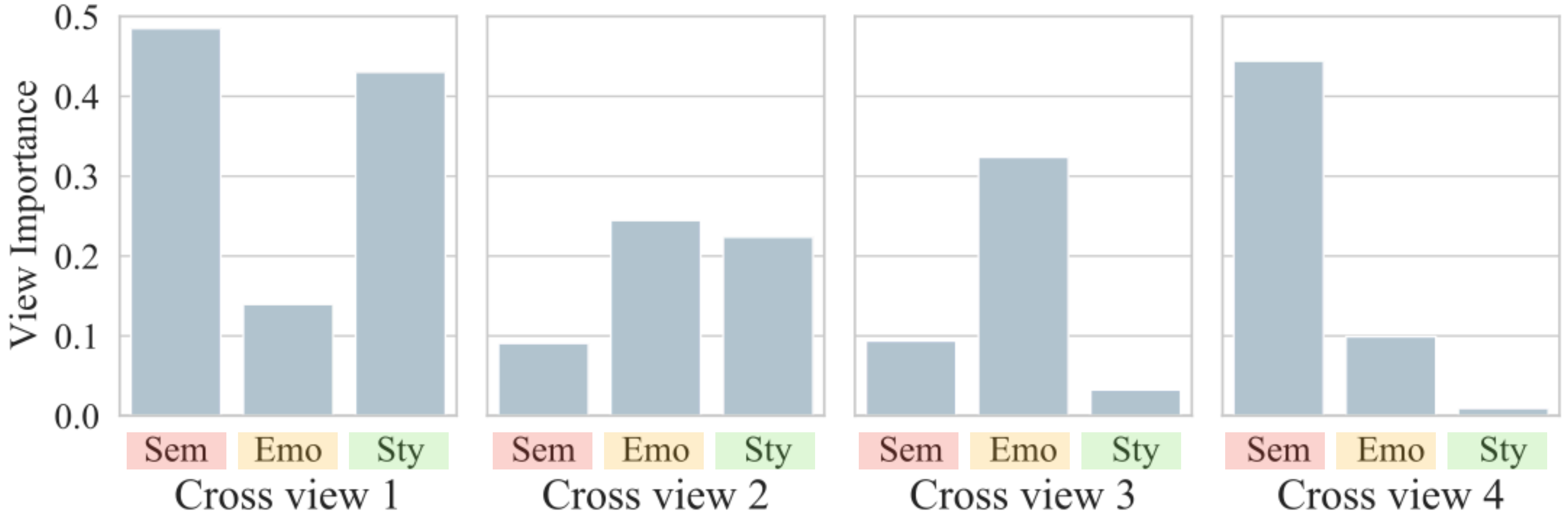


Fig. 5. Each figure indicates importances of different views in a cross-view interaction.

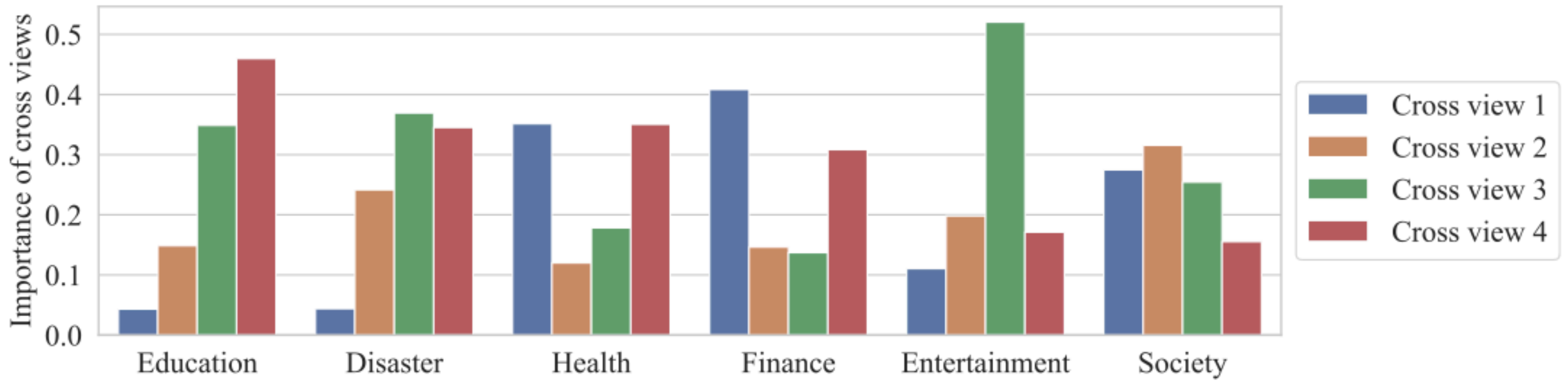


Fig. 6. Various importances of four cross-view interactions for different domains.

Experiments

Effectiveness of Domain Label Completion

Target News		Trump nearly fainted during his speech and cancelled his subsequent trip. A symptom of COVID-19?
Domain	**Similarity v**	**Representative Example**
Science	0.02	NASA used the Nuclear Spectroscopy Telescope to photo the spiral galaxy 1068 in the Cetus.
Military	0.04	U.S. sends 35 medical ships.
Edu.	0.01	A student admitted to Harvard University.
Disaster	0.02	The US "World Journal" reported a five-level fire in a restaurant.
Politics	0.33	US deaths from COVID-19 exceed 100k.
Health	0.21	The animal experiment of Oxford's COVID-19 vaccine failed.
Finance	0.12	Pfizer's stocking price rose 15%, boosted by the company's COVID-19 vaccine news.
Ent.	0.09	10 more people tested positive for COVID-19 in Italian Serie A.
Society	0.16	A COVID-19 carrier refused security check at the airport.

Experiments

Research Questions

- Does proposed M3FEND outperform other approaches in different datasets?
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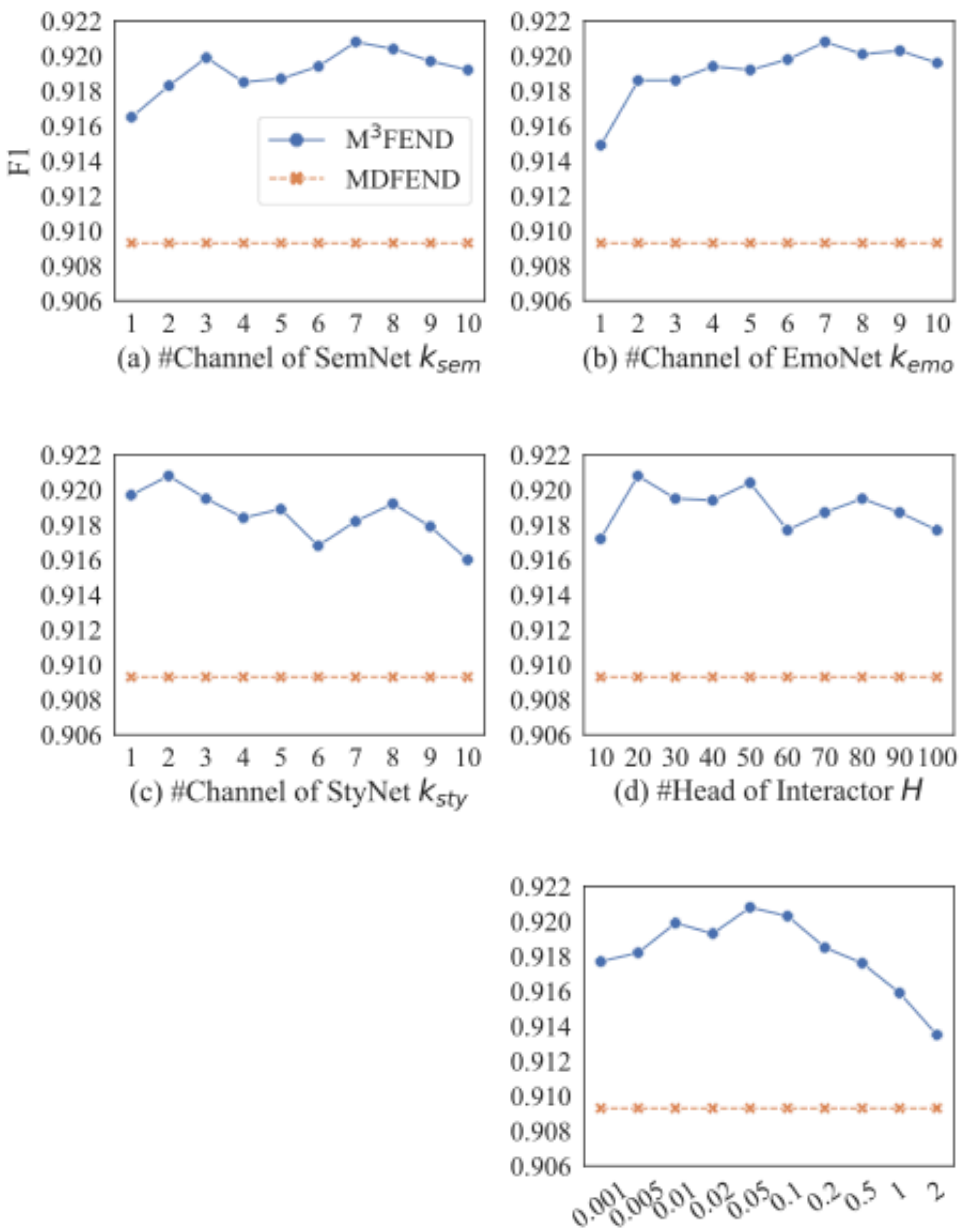
Experiments

Ablation Study

- Observe that even the worst setting in (a)-(d) which is better than MDFEND on the Ch-6 dataset.
- Observe that the performance first increases and then decreases rapidly as β varies and demonstrates a bell-shaped curve.
  - A big β indicates that the memory module could quickly forget historical samples and focus on most recent samples, which leads to overfitting on recent samples.



(a) #Channel of SemNet k_{sem}
(b) #Channel of EmoNet k_{emo}
(c) #Channel of StyNet k_{sty}
(d) #Head of Interactor H
(e) *beta*

Conclusion

of M3FEND

- Analyzed two challenges in multi-domain fake news detection.
  - Domain shift & Domain labeling incompleteness.
- Proposed a novel Memory-guided Multi-view Multi-domain FND Framework (M3FEND).
  - Firstly extracted news representations from multiple views and automatically modeled cross-view interactions, then proposed a Domain Adapter to aggregate cross-view representations for prediction to tackle domain shift.
  - Proposed a Domain Memory Bank to discover potential domain labels and model domain characteristics.

Comments

of M3FEND

- Multi-domain work
- Domain labeling incompleteness
  - Use similarity with other domain news to obtain domain distribution.
- Domain shift
  - Generate cross-view combinations, then adaptively to pay attention on it.
- Use word, emotion, style three views to represent news representation.
  - May can seen as kind of modality to consider in multi-modal works.