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Adversarial Active Learning based Heterogeneous Graph Neural Network for Fake News Detection

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210928 Chia-Chun Ho

Outline

Introduction

Related Work

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Introduction

Fake news detection cases

- Like Brexit and 2016 US presidential election, a lot of fake news is spread on various social platforms during the election. (e.g., on Facebook).
- In the economic field, the extreme sensitivity of the capital market has caused it to suffer from fake news.
  - $130 billion is wiped out in stock value after a piece of fake news claimed that then president Barack Obama was injured in an explosion.
- In public safety affairs, people's responses to emergencies, from natural disasters to terrorist attacks, have been disrupted by the spread of false news online.

Introduction
Detecting fake news on social media

- Fake news is written and published intentionally, so the content is carefully camouflaged.
  - Although the fake news may account for only 1% of news articles, but it's sufficient for the purpose.
  - This makes it difficult to detect fake news simply based on news articles.
- Fake news spreads much faster than real news.
  - Many people retweeted falsehood than they did the truth on Twitter.
  - Therefore, the detection of fake news has high requirements for timeliness.

Introduction

Detecting fake news on social media

- It's expensive and time-consuming to check and label the credibility of news articles by experts manually.
- Fake news detection methods requiring a large number of labels are not practical in the real world.

Introduction

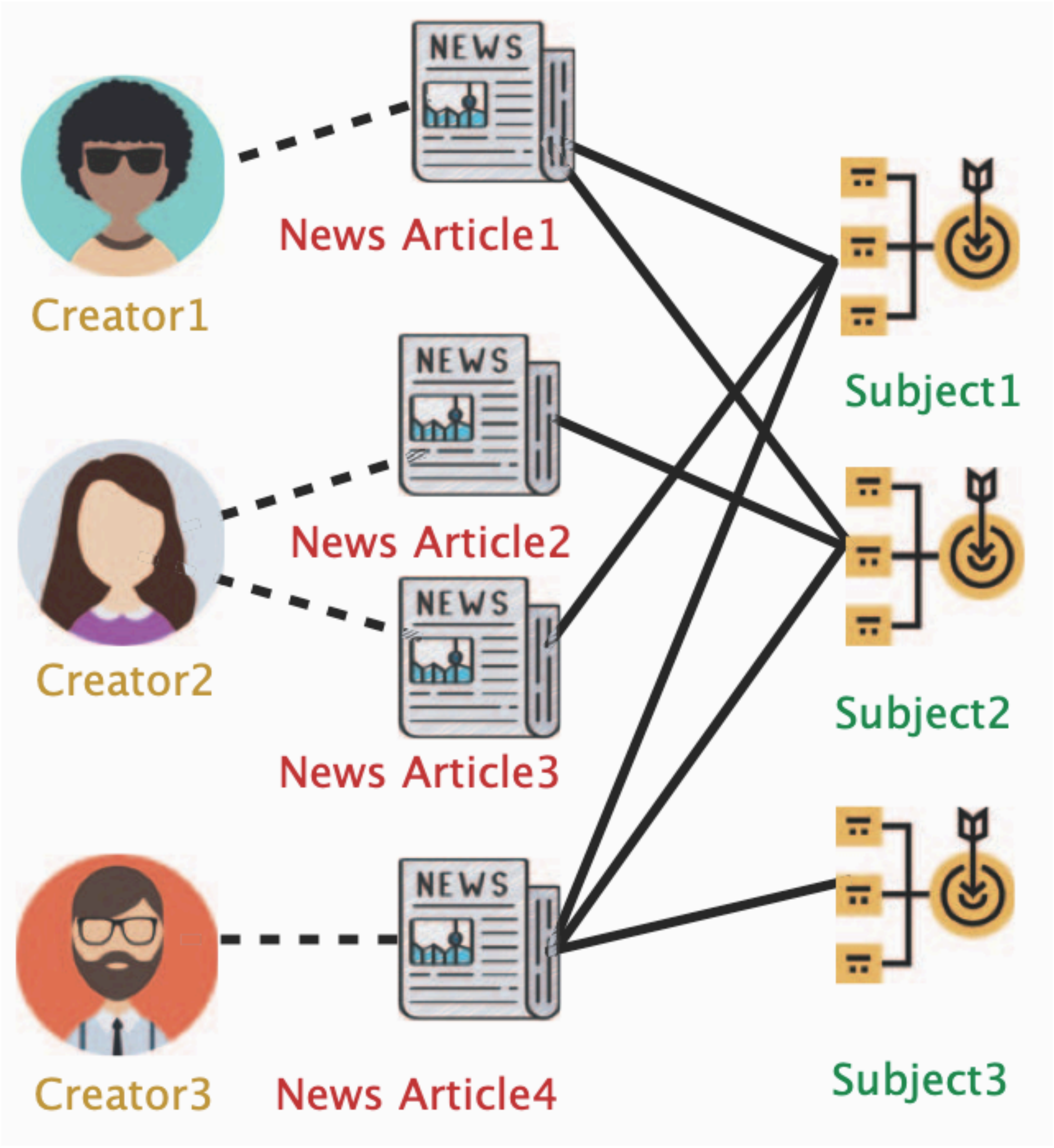
News articles on social media

- News doesn't exist independently in the form of articles.
- In fact, there are many entities related to news articles, such as news creators, news subjects and so on.
- These different types of entities and their relationships provide a more comprehensive perspective on identifying news articles.

Introduction

Heterogeneous Information Network

- In addition to the information provided in the news article, able to collect profile information of news creators from social networks and other supplementary knowledge libraries.
- For the news subjects, the background and auxiliary knowledge can be collected to support the fake news detection.

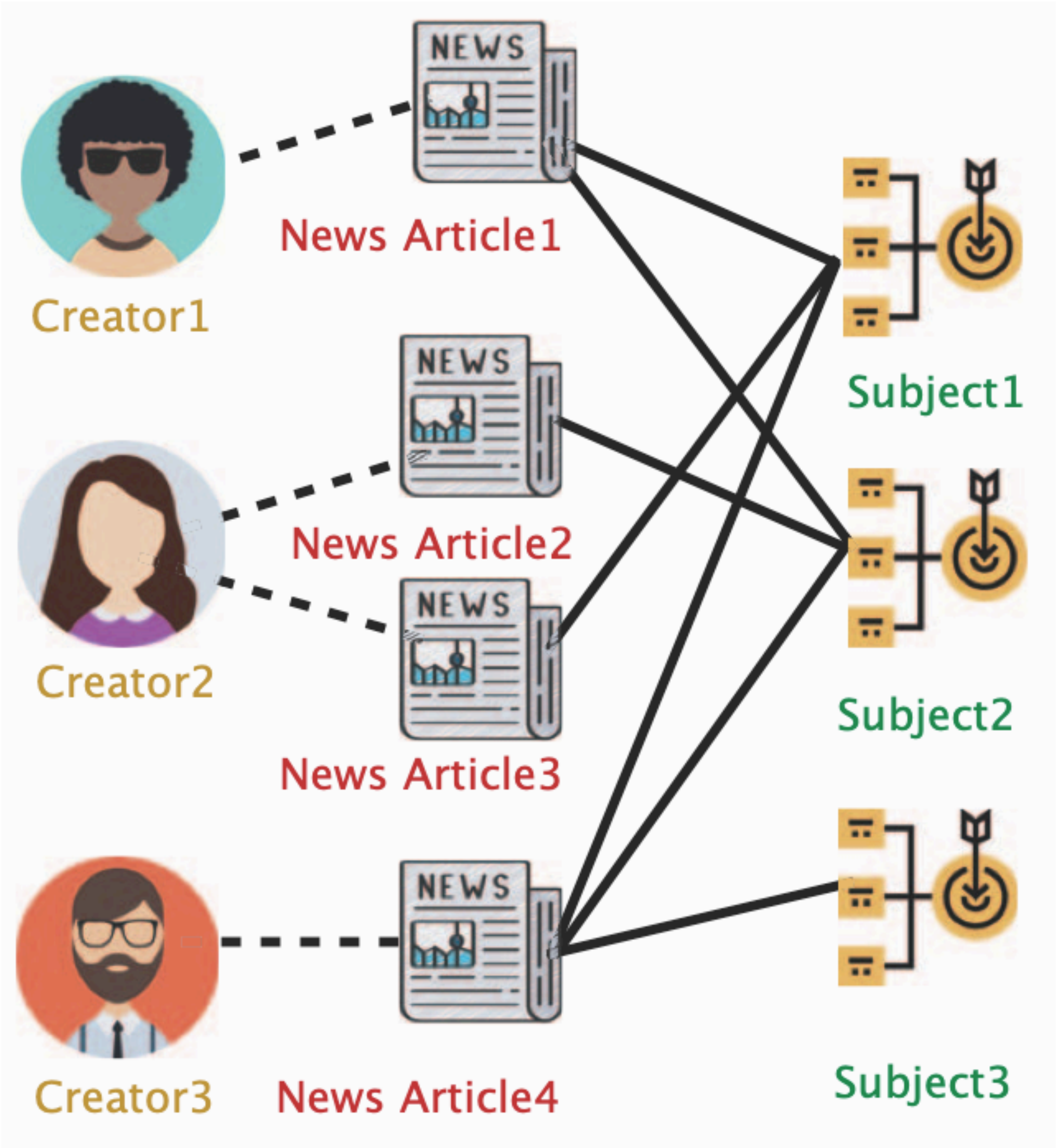


News oriented heterogeneous information network (News-HIN)

Introduction

Heterogeneous Information Network

- With the support of a News-HIN, fake news detection task can be formulated as the node classification problem.
- In this way, more sufficient information and knowledge can be used to check the credibility of news articles.



News oriented heterogeneous information network (News-HIN)

Introduction

Main challenges of fake news detection in a News-HIN

- Paucity of Training data
  - Fake news appears and spreads very quickly. The real-time nature of news also makes outdated labels worthless.
  - Fake news detection often faces the challenge of lacking valuable training data.
  - This requires that models can effectively detect potential fake news with the support of a small amount of training data.

Introduction

Main challenges of fake news detection in a News-HIN

- Heterogeneity
  - Multiple node types in News-HIN, which can provide key signals for identifying fake news article nodes.
  - At the same time, learning effective node representations in a News-HIN considering both structural and type information is non-trivial.

Introduction

Adversarial Active Learning-based Heterogeneous Graph Neural Network (AA-HGNN)

- The proposed framework is built on an active learning framework, where a classifier and a selector are included.
- By continuously querying high-value candidate nodes for classifier training and tuning, excellent performance can be achieved with a small amount of labeled data.
- HGNN with a novel Hierarchical Graph Attention (HGAT) mechanism is utilized in both the classifier and the selector.
- Based on two-level attention mechanism (node-level & schema-level), HGAT can get the optimal combination of different types of neighbors in a hierarchical manner.

Introduction

Adversarial Active Learning-based Heterogeneous Graph Neural Network (AA-HGNN)

- The HGAT-based classifier is responsible for conducting classification on news article nodes.
- The HGAT-based selector is used to evaluate the predicted label from the classifier for high-value selection, the selected candidate nodes will become part of the training set via expert labeling.
- The classifier and the selector are trained based on adversarial learning, with the improvement of the predicted label quality by the classifier, the evaluation ability of the selector will be improved to continuously select better candidates.
- AA-HGNN has no limitation on the structures of News-HINs, thus it has good generalizability and can solve the third challenge well.

Introduction

Contributions

- First to apply adversarial active learning to fake news detection, which can achieve excellent detection performance with much less training data.
- Propose a novel adversarial active learning-based framework AA-HGNN which can handle the heterogeneity of News-HINs effectively through a two-level attention mechanism.
- AA-HGNN is applicable to HINs with different schemas.

Related Work

of fake news detection

- Content-based fake news detection is based primarily on the deep mining of news content.
  - ('14-'15) extract the knowledge, a set of (Subject, Predicate, Object) triples, from the news content and assess the authenticity of news by comparing them with real knowledge.
- Writing style is extracted and utilized to measure the credibility of news.
  - ('15) employs rhetorical structure theory to evaluate the authenticity in discourse level.
  - ('17) capture the sentiment and readability of the news content to access the extent of falsehood.

Related Work

of fake news detection

- Some methods use not only the news content, but also other information related to the news.
- ('18) utilize LSTM and a hierarchical attention mechanism to detect rumors, which makes use of social information through the proposed social feature.
- ('19) study the explainable detection of fake news with the support of both news contents and user comments.
- ('16) evaluate news credibility within a graph optimization framework.
- Methods based on matrix factorization ('19), tensor factorization ('18), and RNN ('17, '18) are proposed to work on the news-oriented networks.

Concept and Problem Definition

Terminology Definition

- News Oriented Heterogeneous Information Networks (News-HIN)
  - Defined as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$
  - The node set $\mathcal{V} = \mathcal{C} \cup \mathcal{N} \cup \mathcal{S}$ (Creator, News, Subject).
  - The link set $\mathcal{E} = \mathcal{E}_{c,n} \cup \mathcal{E}_{n,s}$ (Creator-News: Write, News-Subject: Belongs to)

Concept and Problem Definition

Terminology Definition

- News Articles
  - Refer to the news content post on social media or public platforms.
  - Represented as $\mathcal{N} = \{n_1, n_2, \cdots, n_m\}$, for each news article n_i, it contains its textual contents.
  - The credibility label of n_i takes value from the label set $\mathcal{Y} = \{Fake, Real\}$

Concept and Problem Definition

Terminology Definition

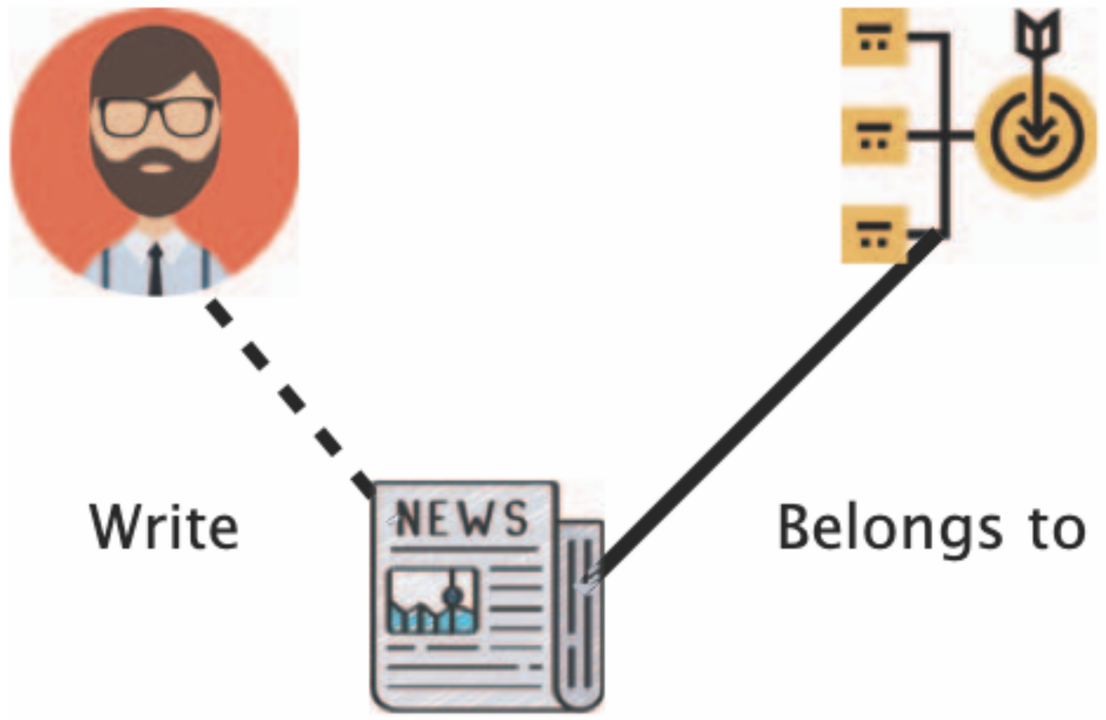
- Subjects
  - Subjects denote the central ideas of news articles, which normally are the main objectives of writing news articles.
  - Represented as $\mathcal{S} = \{s_1, s_2, \cdots, s_k\}$, for each subject s_i, it contains its textual description.

Concept and Problem Definition
Terminology Definition

- Creators
    - Creators denote people who write news articles.
    - Represented as $\mathscr{C} = \{c_1, c_2, \cdots, c_n\}$, for each creator c_i, it contains the profile information.
    - In dataset, the creators have the profile containing their titles, political party membership, and geographical residential locations. The profile information can be described by a sequence of words.

Concept and Problem Definition

Terminology Definition



- News-HIN Schema
  - The schema of News-HIN serves for learning the importance of nodes and links with different types.
  - The schema of the given News-HIN can be represented as $S_{\mathscr{G}} = (\mathscr{V}_T, \mathscr{E}_T)$.
  - $\mathscr{V}_T = \{\phi_n, \phi_c, \phi_s\}$
  - $\mathscr{E}_T = \{Write, Belongs\ to\}$

Concept and Problem Definition

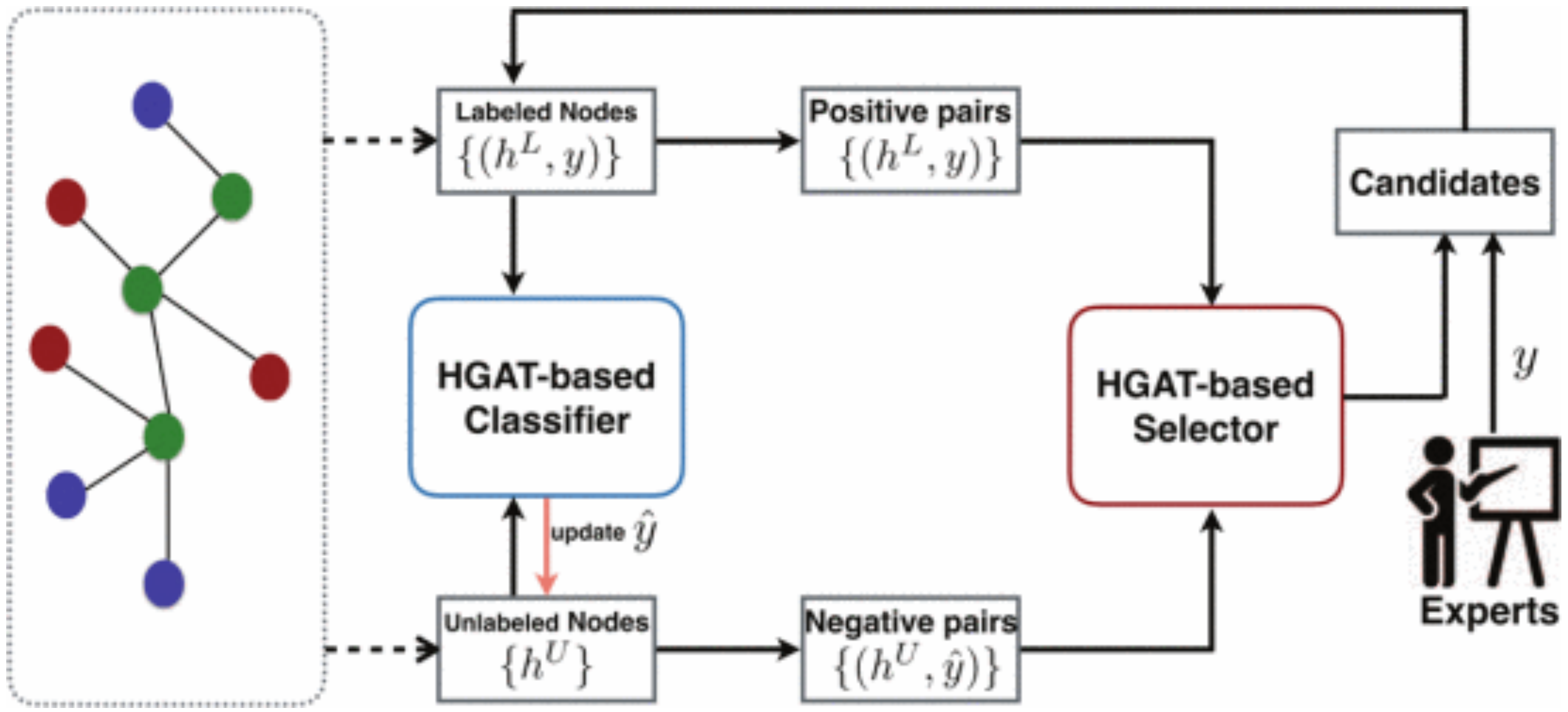
Problem Definition

- Given a News-HIN, the fake news detection problem aims at learning a classification function $f : \mathcal{N} \rightarrow \mathcal{Y}$ to classify news article nodes with labels can be grouped as a labeled set $\mathcal{L}$ and the rest news article nodes $\mathcal{U} = \mathcal{N} \backslash \mathcal{L}$.

- Based on the active learning setting, also allowed to query for labels of news article nodes in $\mathcal{U}$ with upper limit budget b.

- Also want to proposed a mechanism to achieve an optimal query set $\mathcal{U}_q$ to improve the classification function $f : \mathcal{N} \rightarrow \mathcal{Y}$.

Proposed Method
Model Overview

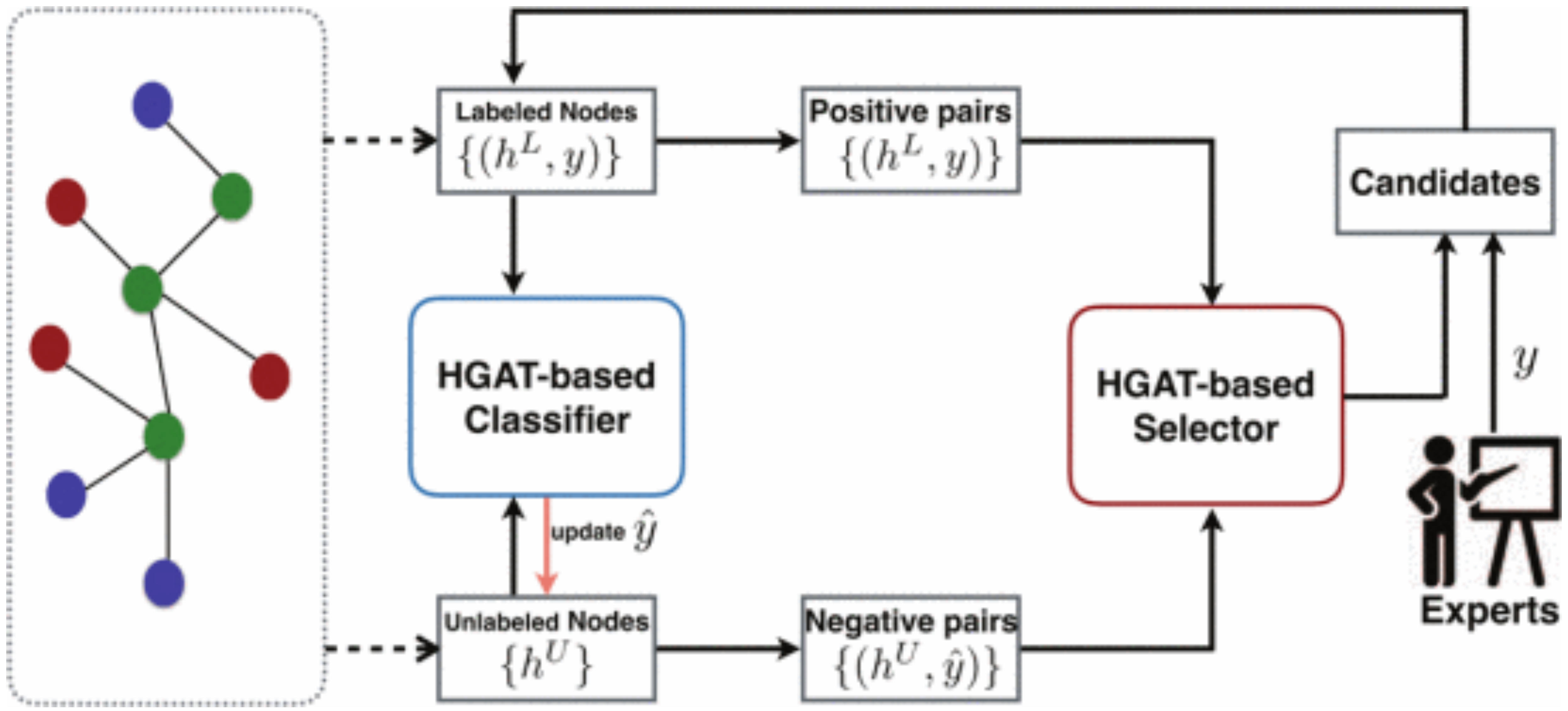


Overall framework

Hierarchical Graph Attention Neural Network (HGAT)

Proposed Method

Model Overview

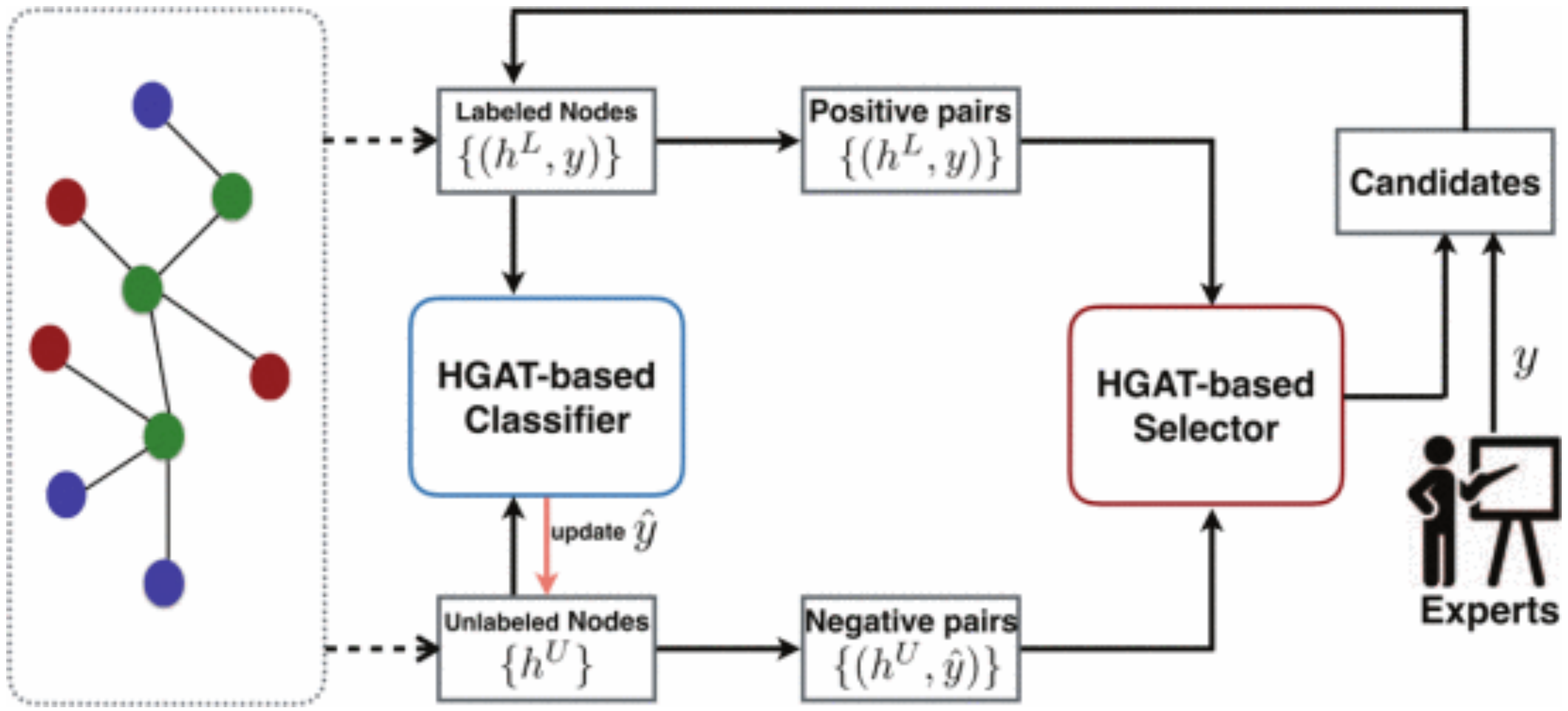


Overall framework

- AA-HGNN consists of two major components:
    - HGAT-based classifier
    - HGAT-based selector

Proposed Method

Model Overview

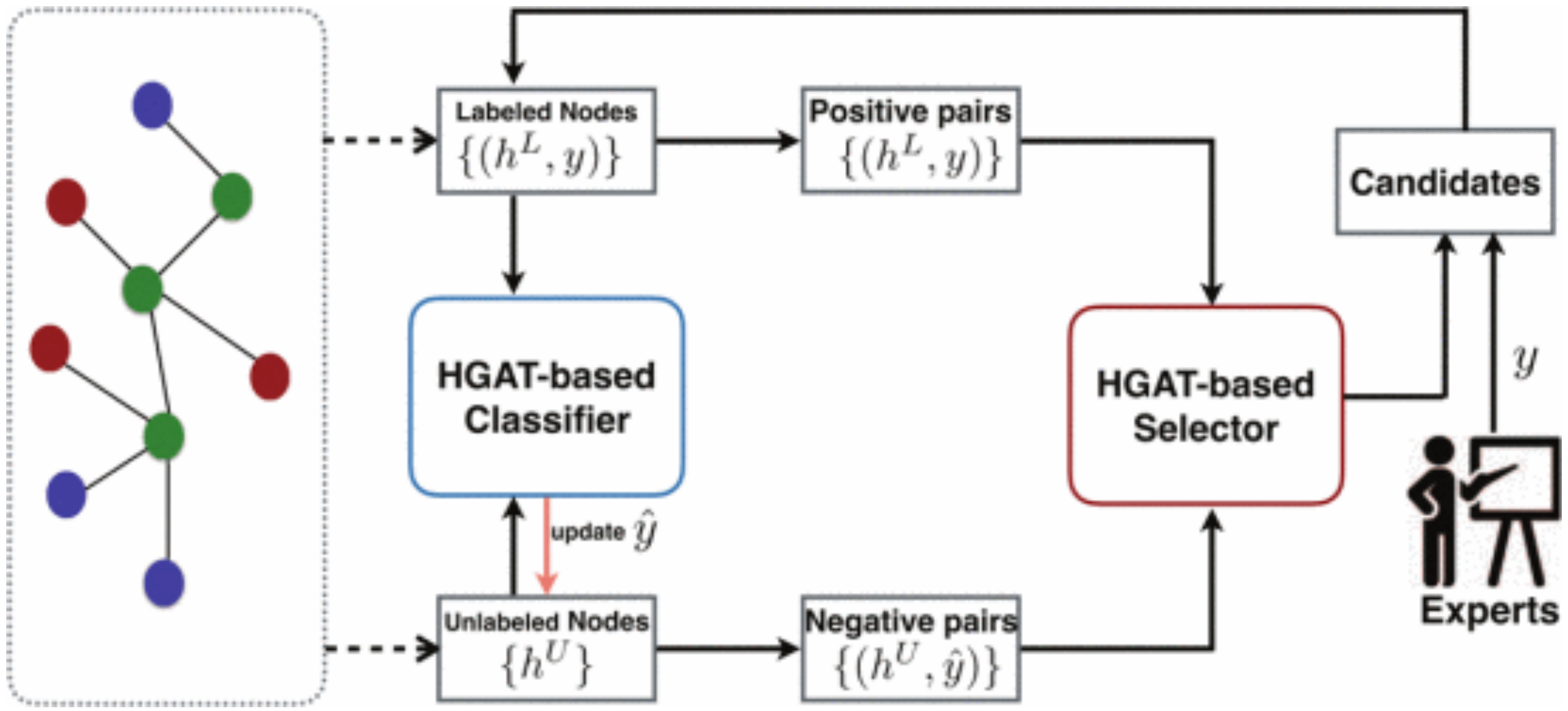


Overall framework

- News-HIN is the input of AA-HGNN.
- h^L and h^U denote the initial feature of a labeled node and an unlabeled node respectively.

Proposed Method

Model Overview

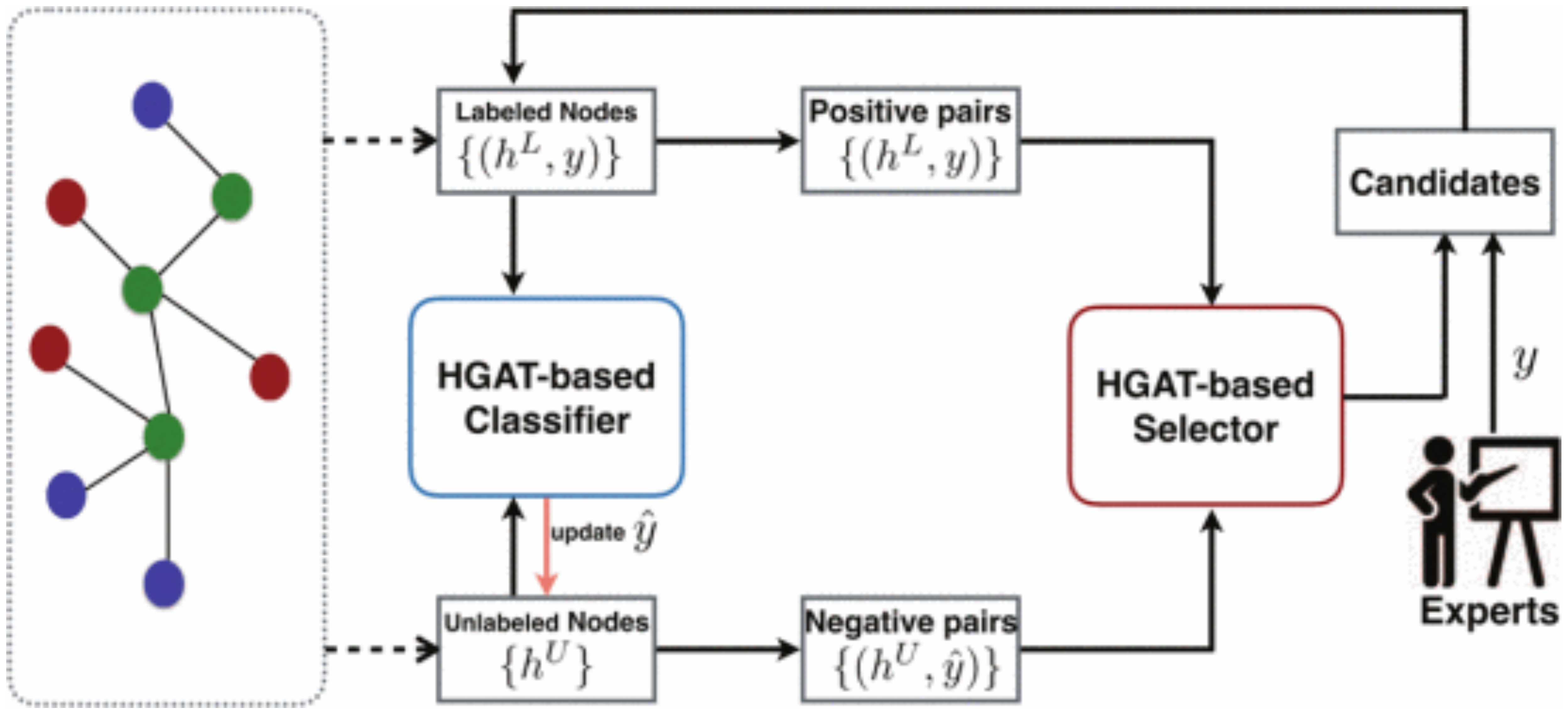


Overall framework

- Classifier is trained with both labeled and unlabeled data to predict labels $\{\hat{y}\}$ for unlabeled news article nodes.
- Selector evaluates the quality of predicted labels and selects high-value candidates from them based on a query strategy.

Proposed Method

Model Overview



Overall framework

- Take the pairs of labeled nodes and their ground-truth labels $\{y\}$ as positive samples, and the pairs of unlabeled nodes and their predicted labels $\{\hat{y}\}$ are used as negative samples.
- A portion of positive and negative pairs are sampled to train the HGAT-based selector.

Proposed Method

Hierarchical Graph Attention Neural Network (HGAT)

- The novel HGAT employs a two-level attention mechanism including node-level attention and schema-level attention.

- Node-level attention is responsible for learning the weights of neighbors belong to the same type and aggregates them to get the type-specific neighbor representation.

- Schema-level attention enables HGAT to learn the information of node types and get the optimal weighted combination of the type-specific neighbor representations.

Hierarchical Graph Attention Neural Network (HGAT)

Proposed Method

Node-level attention

- In order to enable the attention mechanism to output comparable and meaningful weights between different types of nodes.

- First utilize a type-specific transformation matrix to project features with different dimensions into the same feature space.

- $h'_{n_i} = \mathbf{M}^{\phi_n} \cdot h_{n_i}$

Hierarchical Graph Attention Neural Network (HGAT)

Proposed Method

Node-level attention

- The h'_{n_i} is the projected feature of node n_i.
- Through the type-specific projection operation, the feature space of nodes with different types can be unified where the self-attention mechanism can work on to learn the weight among various kinds of nodes.
- Node-level attention can learn the importance $e_{ij}^{\phi_t}$ which means how important node t_j will be for n_i. The importance of the node pair (n_i, t_j) can be formulated as follows:
- $e_{ij}^{\phi_t} = att(h'_{n_i}, h'_{t_j}; \phi_t)$

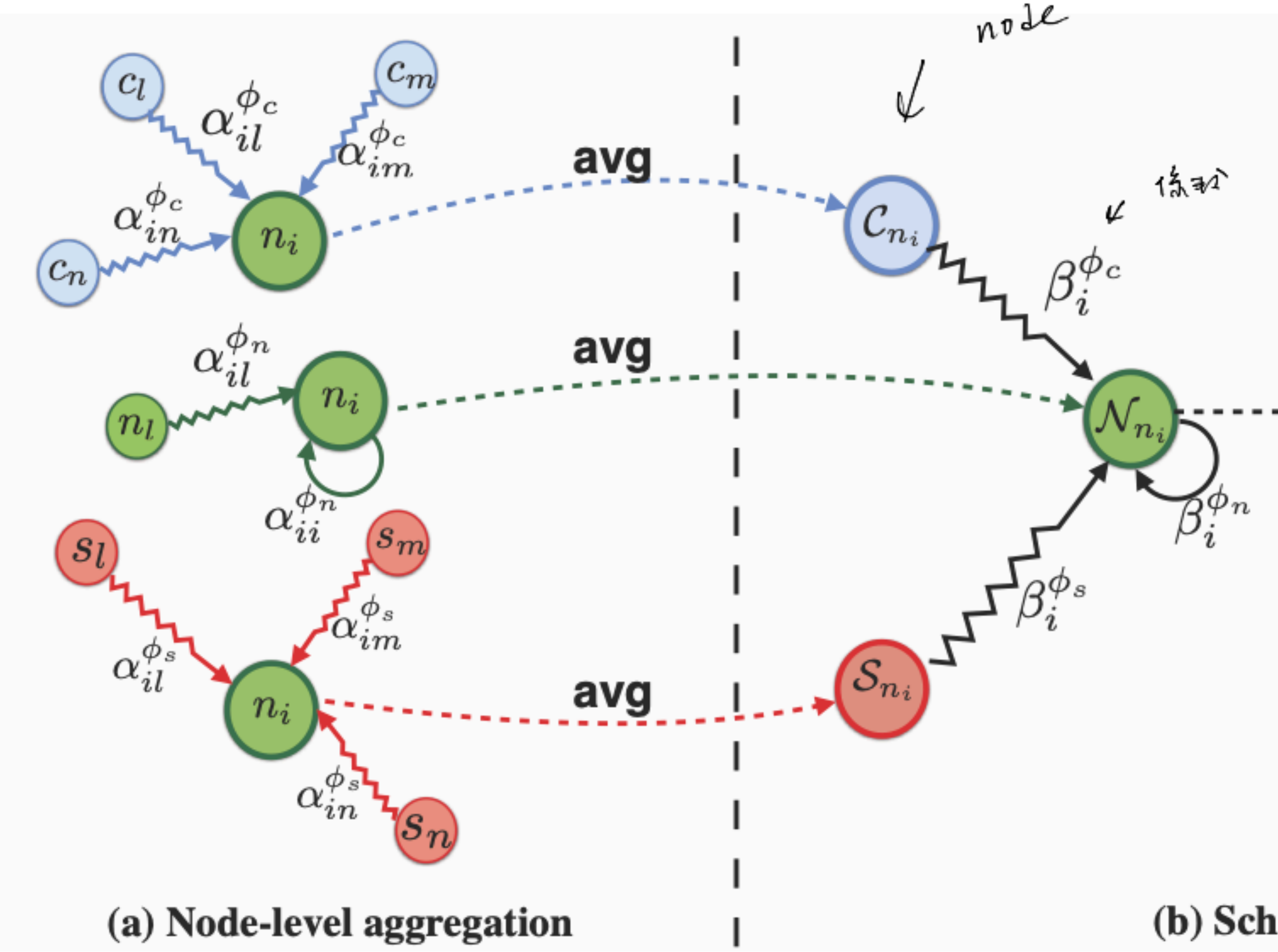
Hierarchical Graph Attention Neural Network (HGAT)

Proposed Method

Node-level attention

- $e_{ij}^{\phi_t} = att(h'_{n_i}, h'_{t_j}; \phi_t)$
- $\alpha_{ij}^{\phi_t} = \text{sofmax}_j(e_{ij}^{\phi_t}) = \dfrac{exp(e_{ij}^{\phi_t})}{\sum_{t_k \in neighbor_{n_i}} e_{ik}^{\phi_t}}$
- $T_{n_i} = \sigma(\sum_{t_j \in neighbor_{n_i}} \alpha_{ij}^{\phi_t} \cdot h'_{t_j})$

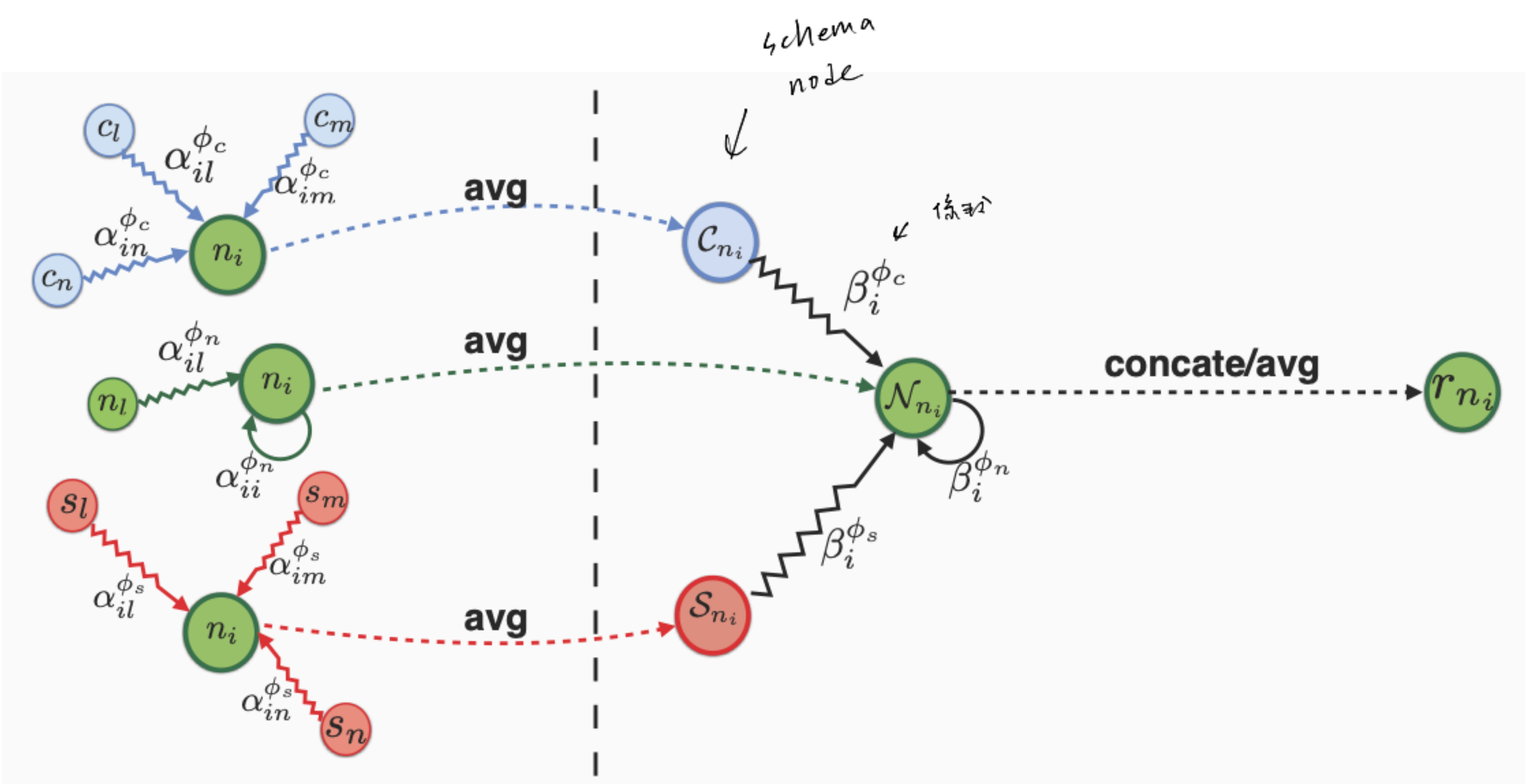
schema node



Proposed Method

Schema-level attention

- Through the node-level attention, we fuse information from neighbor nodes with the same type into the representation of a schema node.
- Here, the schema-level attention is proposed to learn the importance of different schema nodes, and finally use the learned coefficients for weighted combination.



(a) Node-level aggregation
(b) Schema-level aggregation

Proposed Method

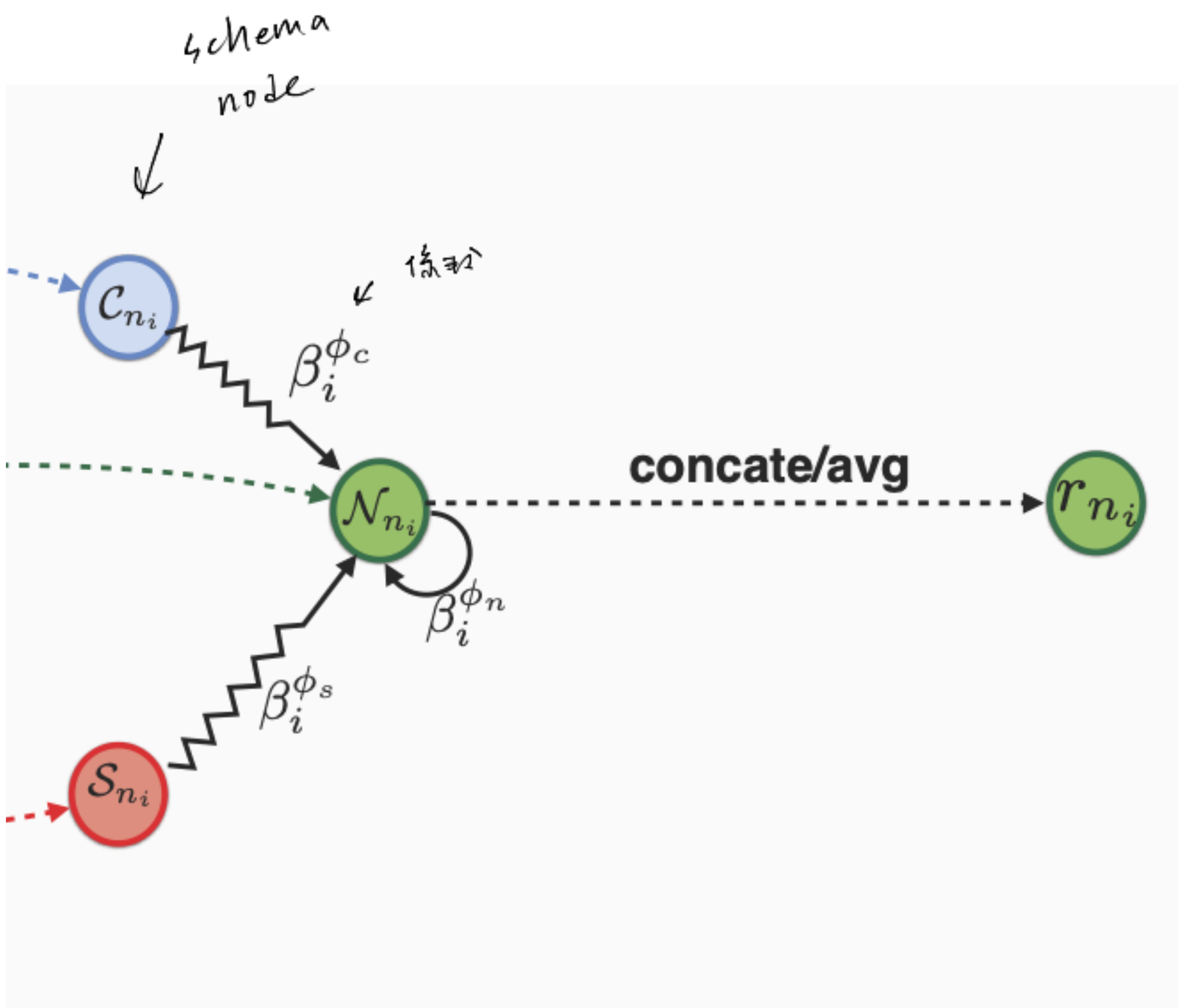
Schema-level attention

- In order to obtain sufficient expressive power to calculate the attention weights between schema nodes, one learnable linear transformation is applied to the schema nodes.

- The schema-level attention *schema* is a single-layer feedforward neural network applying the activating function Sigmoid.

- For the schema node T_{n_i}, the importance of it can be denoted as $w_i^{\phi_t}$:

- $w_i^{\phi_t} = schema(\mathbf{W}T_{n_i}, \mathbf{W}\mathcal{N}_{n_i})$

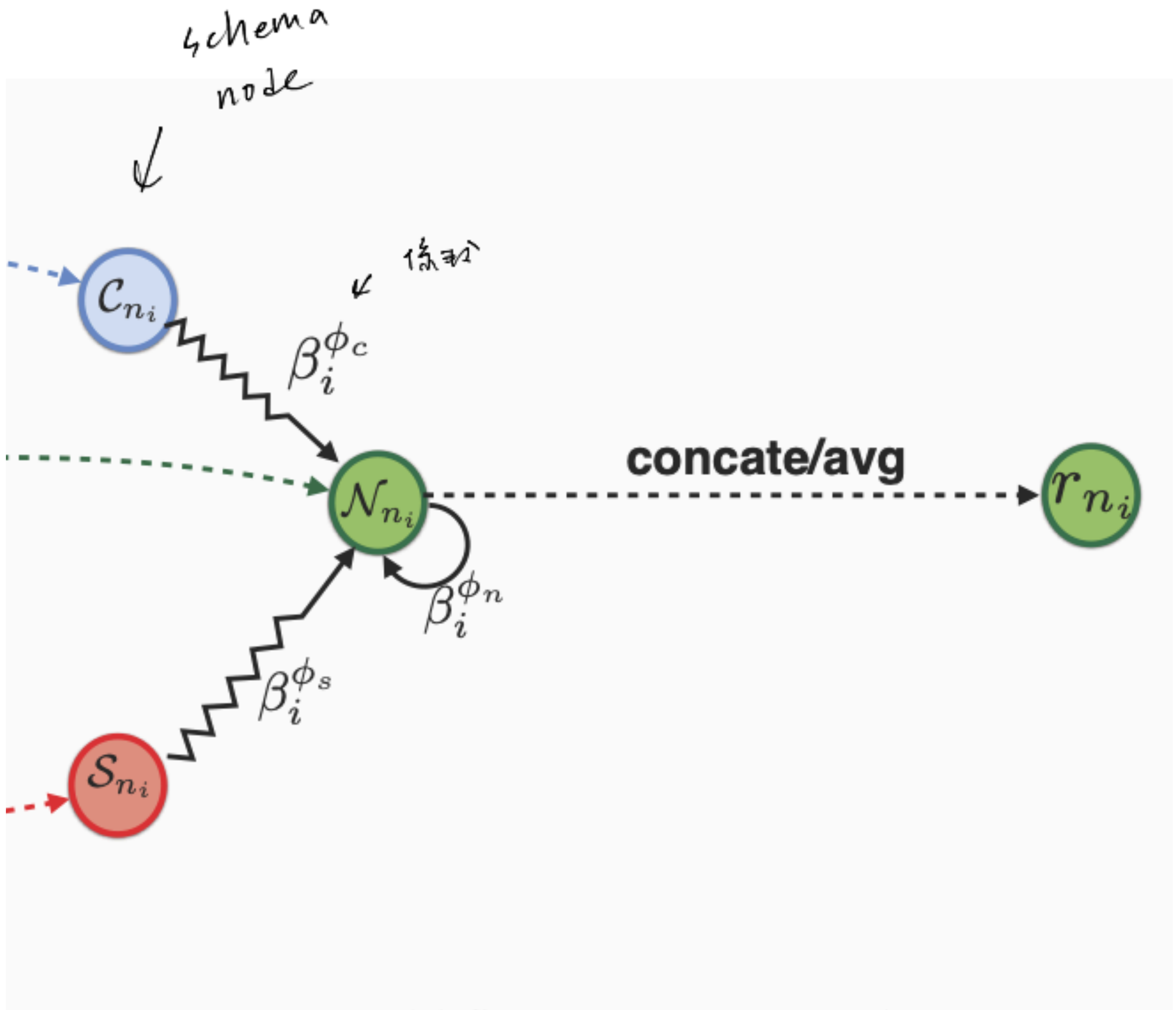


(b) Schema-level aggregation

Proposed Method

Schema-level attention

- $w_i^{\phi_t} = schema(\mathbf{W}T_{n_i}, \mathbf{W}\mathcal{N}_{n_i})$
- $\beta_i^{\phi_t} = \mathrm{softmax}_t(w_i^{\phi_t}) = \dfrac{\exp(w_i^{\phi_t})}{\sum_{\phi \in \mathcal{V}_T} \exp(w_i^{\phi})}$
- Based on the learned coefficients, we can fuse all schema nodes to get the final representation:
- $r_{n_i} = \sum\limits_{\phi_t \in \mathcal{V}_T} \beta_i^{\phi_t} \cdot T_{n_i}$

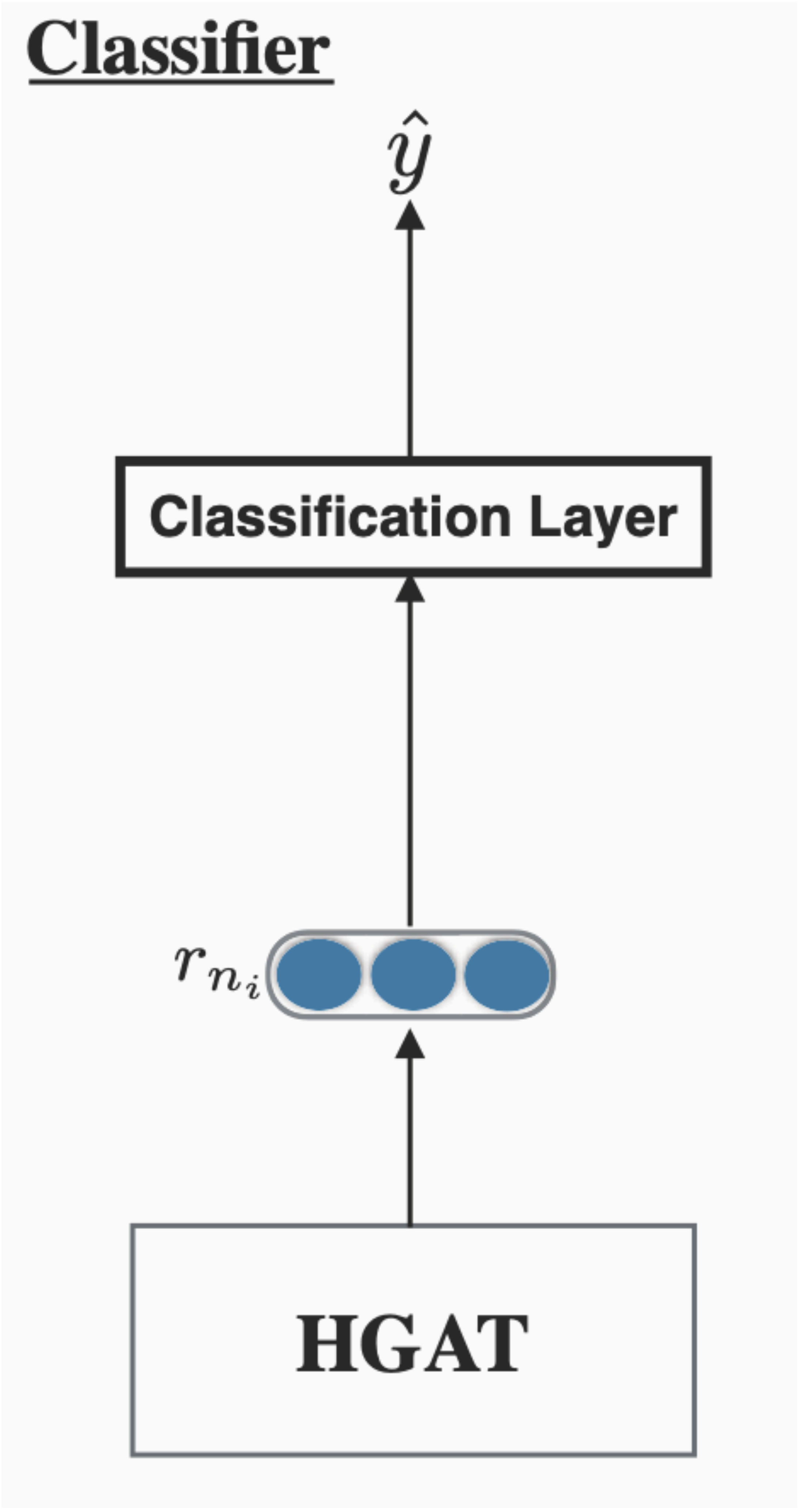


(b) Schema-level aggregation

Proposed Method

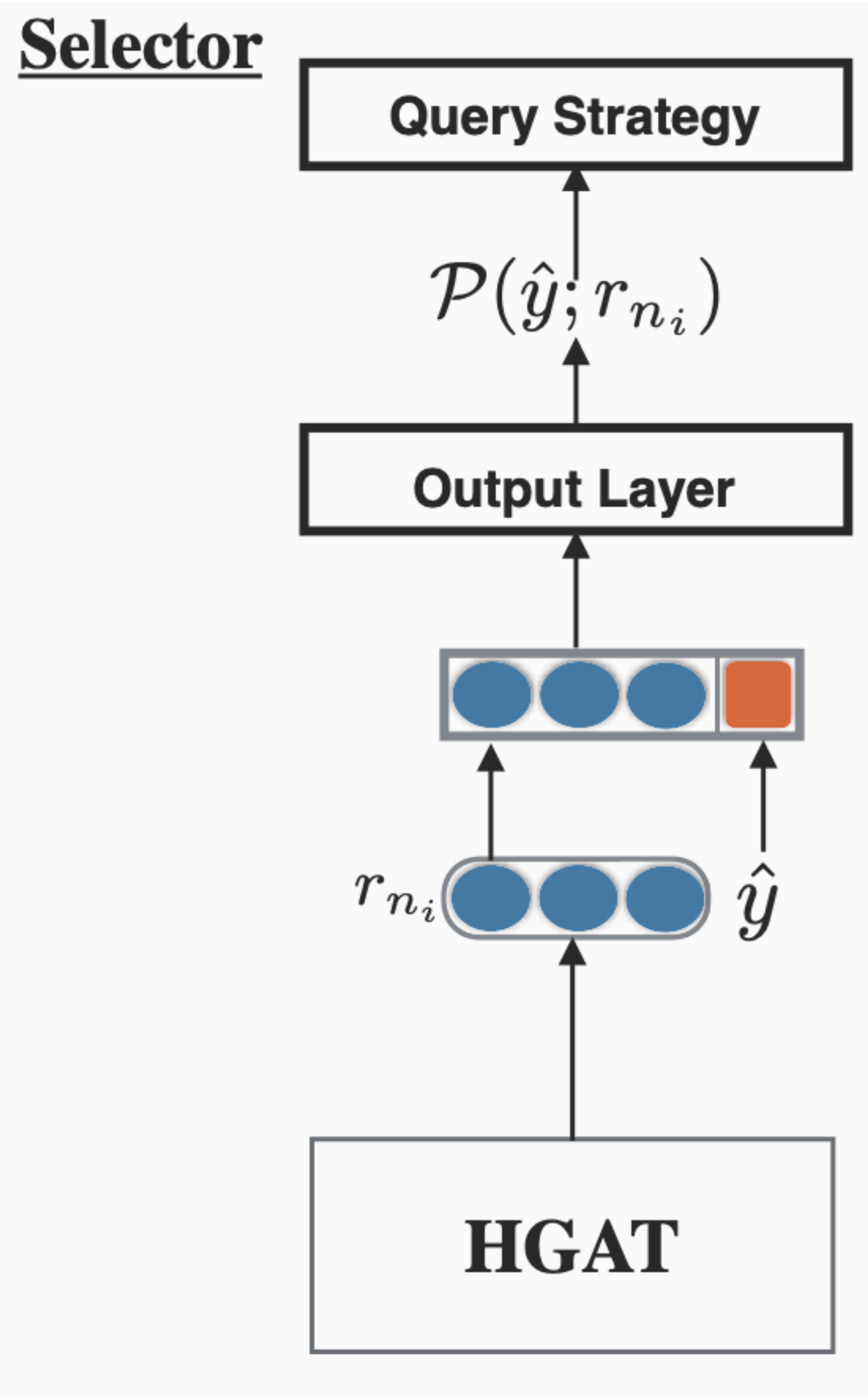
HGAT-Based Classifier

- HGAT and a classification layer constitute a HGAT-based classifier.
- The input of HGAT-based classifier is the same as HGAT, which are the initial feature vectors of nodes. The classification layer can output the predicted labels $\{\hat{y}\}$ of unlabeled news article nodes.
- Optimization objective function of the HGAT-based classifier can leverage the cross-entropy loss minimization.
- $$Loss_{classifier} = -\sum_{n_i \in \mathcal{N}_L} (y_{n_i} \log(p_{n_i}) + (1 - y_{n_i}) \log(1 - p_{n_i}))$$



Proposed Method
HGAT-Based Selector

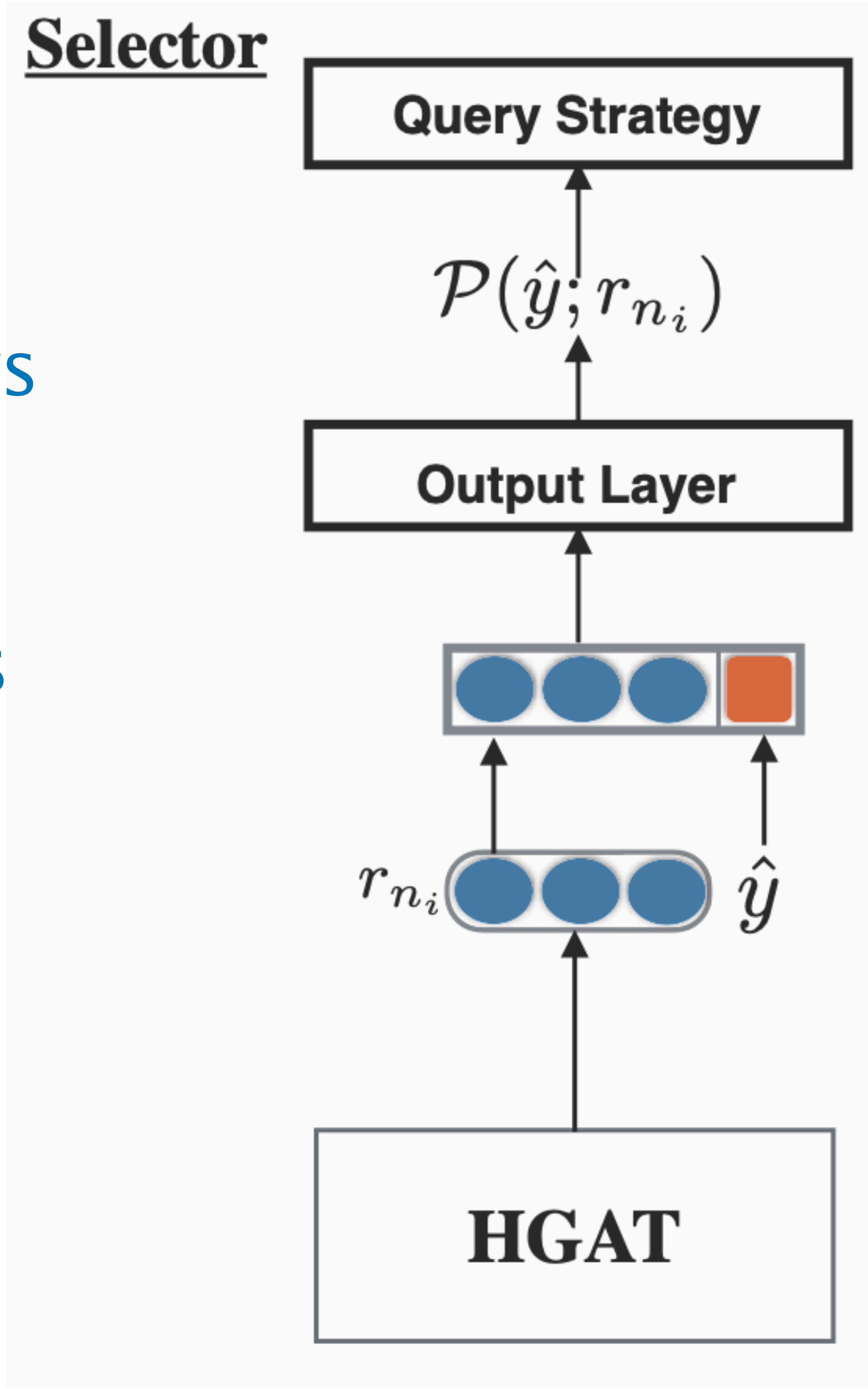
- The inputs of the layers of HGAT are the initial feature vectors $\{h\}$.
- Based on the learned representation r_{n_i}, then concatenate r_{n_i} with the predicted label $\hat{y}$ (or the ground-truth label y of the labeled node).
- Denote concatenated vector as z_{n_i}:
  - $z_{n_i} = [r_{n_i}, \hat{y}]$



Proposed Method

HGAT-Based Selector

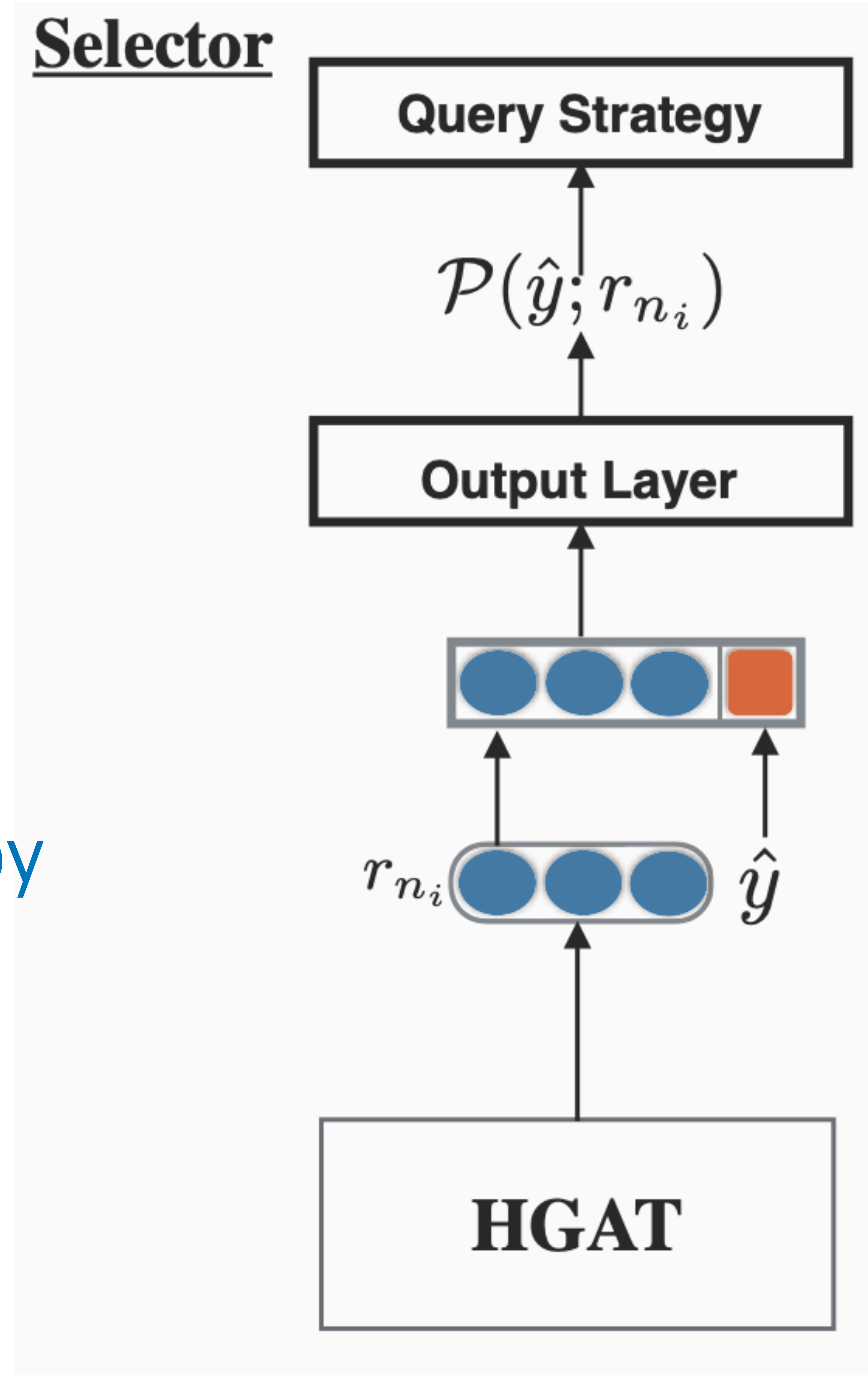
- The purpose of the HGAT-based selector is to evaluate the probability that how likely the z_{n_i} is from the set of labeled news article nodes $\mathcal{N}_L$.
- A higher possibility represents that a news article node matches the predicted label better. At the same time, if a node doesn't match the predicted label, it is likely to indicate that the predicted label is wrong.
- The output layer is responsible for predicting the probability $\mathscr{P}(\hat{y}; r_{n_i})$, use a logistic regression layer as the output layer.



Proposed Method

HGAT-Based Selector

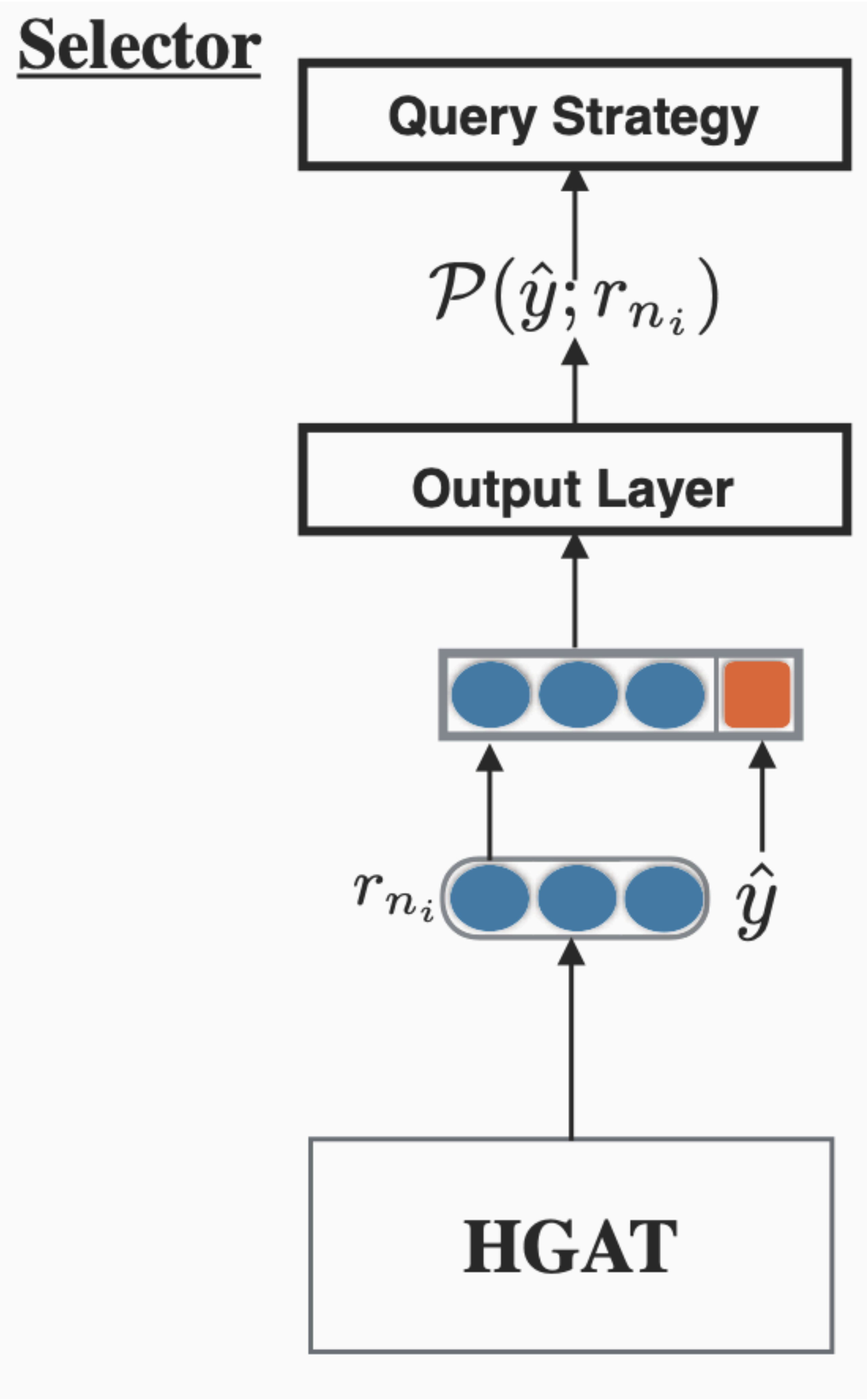
- Sample $z_{n_j}, n_j \in \mathcal{N}_L$ as the positive samples, and the same number of $z_{n_k}, n_k \in \mathcal{N}_U$ are sampled as the negative samples.
- These positive and negative samples constitute the training set for the HGAT-based selector.
- The loss function used by HGAT-based selector is a cross-entropy loss:
  - $Loss_{selector} = -\sum(y\log(\mathscr{P}) + (1-y)\log(1-\mathscr{P}))$



Proposed Method

HGAT-Based Selector

- The rest concatenated vectors of unlabeled news article nodes are in the testing set.
- After training, the HGAT-based selector will output the probability $\mathscr{P}$ for testing samples.
- Lower probability $\mathscr{P}$ indicates that the unlabeled news article node and the predicted label do not match.
- It also represents there is a high probability that the predicted label will be wrong.

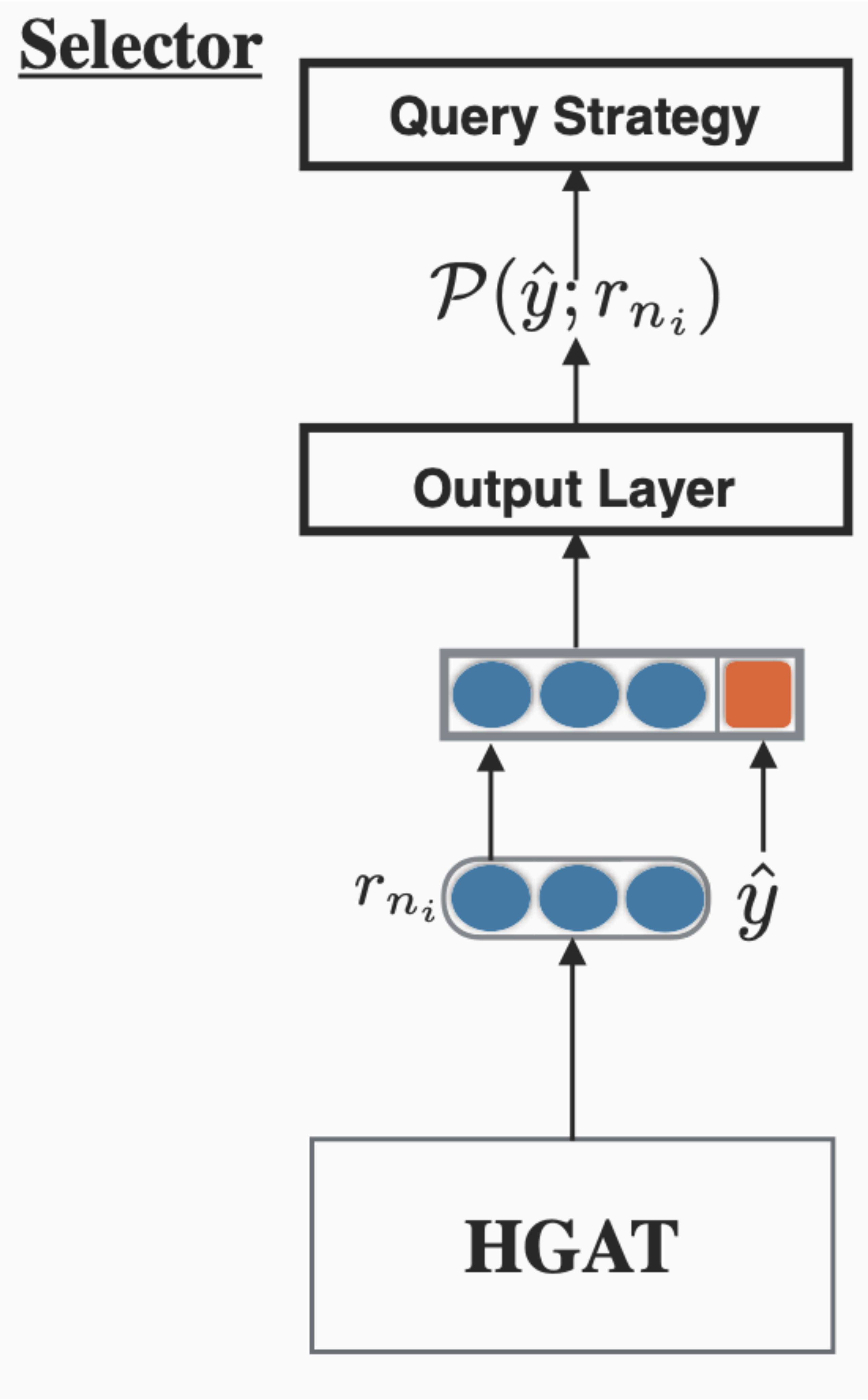


Proposed Method

HGAT-Based Selector

- Obviously, if the news article node we query was not able to be classified correctly by the HGAT-based classifier, then it will be more "informative" than the nodes that have been correctly classified.

- Besides, make it as part of the training set in the next round of training after experts labeling, thereby correcting the misclassified nodes in the test set for similar reasons.



Proposed Method

Adversarial Active Optimization

- In AA-HGNN, the classifier and the selector cooperate in an adversarial active manner.
- Adopt the iterative optimization to train these components in AA-HGNN.
- In each iteration, the HGAT-based classifier and the HGAT-based selector have trained alternately.

Algorithm 1: Adversarial Active optimization of AA-HGNN

Input: The News-HIN $\mathcal{G} = (\mathcal{V}, \mathcal{E})$; The set of labeled news article nodes $\mathcal{N}_L$; The set of unlabeled news article nodes $\mathcal{N}_U$; The query budget b; The query batch size k; Number of samples m;

$\mathcal{U}_q = \emptyset$;
while $|\mathcal{U}_q| < b$ **do**
  ▷ **Optimization for HGAT-based classifier;**
  begin
    Train the HGAT-based classifier on $\mathcal{N}_L$ via Eq.9;
    Predict the labels of nodes in $\mathcal{N}_U$;
    Update the set of predicted labels $\{\hat{y}\}$;
  ▷ **Optimization for HGAT-based selector;**
  begin
    Sample m nodes from $\mathcal{N}_L$ to construct positive samples via Eq.10, i.e., $z_{n_j}, n_j \in \mathcal{N}_L$;
    Sample m nodes from $\mathcal{N}_U$ to construct negative samples via Eq.10, i.e., $z_{n_k}, n_k \in \mathcal{N}_U$;
    Train the HGAT-based selector on positive and negative samples;
    Predict the probability $\mathcal{P}$ via Eq.11;
    Query k candidates based on Definition 6;
  $\mathcal{U}_q = \mathcal{U}_q \cup \{candidates\}$;
  Labeling k candidates by experts;
  $\mathcal{N}_L = \mathcal{N}_L \cup \{candidates\}$;
  $\mathcal{N}_U = \mathcal{N}_U \setminus \{candidates\}$;
return *The set of predicted labels* $\{\hat{y}\}$

Proposed Method

Adversarial Active Optimization

- First train the HGAT-based classifier to output the predicted labels.
- Then the HGAT-based selector will be trained by the predicted labels from the classifier.
- Based on the optimized selector, k candidates will be queried in one iteration and be added to $\mathcal{U}_q$ used as training data in the next iteration.
- Each time k candidates are obtained, the classification performance of the HGAT-based classifier can be improved in the next iteration.

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return *The set of predicted labels* $\{\hat{y}\}$

Proposed Method

Adversarial Active Optimization

- As a consequence, the credibility of predicted labels will be increased.
- Better predicted labels further improve the evaluation performance of the HGAT-based selector.
- Repeat the above iteration until the size of $\mathcal{U}_q$ exceeds the query budget b.

Algorithm 1: Adversarial Active optimization of AA-HGNN

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return *The set of predicted labels* $\{\hat{y}\}$

Experiments

Datasets

PROPERTIES OF THE HETEROGENEOUS NETWORKS

7590 = 6465	PolitiFact Network		BuzzFeed Network	91 = 91
# node	article	14,055	article	182
	creator	3,634	twitter user	15,257
	subject	152	publisher	9
# link	creator-article	14,055	publisher-article	182
	article-subject	48,756	article-twitter user	25,240

- PolitiFact
  - Article, creator, subject; write, belongs to
  - Group the labels {Pants on fire, False, Mostly False} as fake news and group {True, Mostly True, Half True} as real news.
- BuzzFeed (cr/FakeNewsNet)
  - Article, twitter user and publisher

Experiments

Experimental Setup

- For all comparison methods,
  - Use 20% news article nodes as the training set
  - Use 10% of the nodes as the validation set.
  - The testing ratio is fixed as 10%.
- For AA-HGNN, use 1000 nodes to initialize the active learning. The query budget b is 1800 and the query batch size k is 200. In this way, 2800 nodes (20%) are utilized to train AA-HGNN finally.
- Use sklearn.TfidfVectorizer to transform the input features of each type of nodes into a vector with a fixed length.

Experiments

Baselines: Graph neural network methods

- AA-HGNN: the proposed model.
- AA-HGNN$_{entropy}$: query the candidates according to entropy. (Higher its entropy, when $\mathscr{P}$ close to 0.5)
- AA-HGNN$_{random}$: query the candidates randomly.
- HGAT-based classifier: without HGAT-based selector of AA-HGNN (w/o active learning).
- HAN (NAACL'16): employ node-level attention and semantic-level attention to capture the information from all meta-paths.
- GAT (ICLR'16): attention-based GNN for the node classification, but it's designed for homogenous graph, so treat News-HIN as a homogenous graph (ignore the type information).
- GCN (ICLR'17): semi-supervised method for node classification also in homogenous graph.

Experiments

Baselines: Text classification & Network Embedding methods

- SVM: model extracted based on the news article contents with TF-IDF
- Text-CNN (arXiv'14): text classification method based on CNN.
- LIWC ('15): Linguistic Inquiry and Word Count, widely used to extract the lexicons falling into psycho-linguistic categories.
- Label Propagation ('02): based on the network structure.
- DeepWalk (KDD'14): random walk based embedding method, which is designed to deal with the homogeneous network.
- LINE (WWW'15): preserves the local and the global network structure simultaneously.

Experiments
Evaluation Questions

- EQ1: Can AA-HGNN improve fake news detection performance by modeling data as a News-HIN?
- EQ2: Can Hierarchical Graph Attention (HGAT) mechanism handle the heterogeneity of the News-HIN effectively?
- EQ3: Can the active learning setting of AA-HGNN overcome the paucity of training data?
- EQ4: Can adversarial learning between the classifier and the selector significantly help improve the performance?

Experiments
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Experiments

Assessing Impact of News-HIN

	Methods	PolitiFact				BuzzFeed			
		Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
Text	SVM	0.5432	0.4975	0.32	0.3894	0.5398	0.6011	0.5109	0.5523
	LIWC	0.4544	0.4415	0.23	0.3023	0.6137	0.6459	0.5885	0.6175
	Text-CNN	0.5658	0.5873	0.2824	0.3814	0.6317	0.6415	0.6233	0.6322
NE	Label Propagation	0.5796	0.7005	0.1164	0.1996	0.5867	0.6409	0.223	0.3309
	DeepWalk	0.5297	0.4639	0.2881	0.4639	0.3721	0.3083	0.4322	0.3599
	LINE	0.5012	0.4109	0.1215	0.4109	0.5899	0.6123	0.3057	0.4077
GNNs	GAT	0.5765	0.7569	0.0453	0.0854	0.5885	0.654	0.3367	0.4445
	GCN	0.5611	**0.9688**	0.0246	0.048	0.5671	0.6331	0.2674	0.3816
	HAN	0.5867	0.6802	0.2062	0.3165	0.5917	0.7163	0.4677	0.5659
	HGAT-based classifier	0.6154	0.578	0.424	0.4893	0.7022	0.6928	0.6412	0.666
	AA-HGNN$_{random}$	0.5724	0.5152	0.5515	0.5328	0.6843	0.6439	0.6123	0.6277
	AA-HGNN$_{entropy}$	0.5601	0.5022	0.5581	0.5286	0.7161	0.7088	0.6503	0.6783
	AA-HGNN	**0.6155**	0.5661	**0.5804**	**0.5732**	**0.7351**	**0.7211**	**0.6909**	**0.7057**

- Text category: TextCNN > SVM & LIWC in all metrics.
- Text-CNN can better capture the important textual features in news contents by utilizing multiple convolution filters.

Experiments

Assessing Impact of News-HIN

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- Network embedding methods relying on graph structures, all of them achieve a poor recall.

- Low recall means omitting lots of fake news so that they will cause bad social influence.

Experiments

Assessing Impact of News-HIN

	Methods	PolitiFact Accuracy	PolitiFact Precision	PolitiFact Recall	PolitiFact F1	BuzzFeed Accuracy	BuzzFeed Precision	BuzzFeed Recall	BuzzFeed F1
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- News-HIN integrates all heterogeneous available data in the form of a graph structure.
- AA-HGNN, HAN making full use of News-HIN as training data achieve better results.
- Verify that the heterogeneity of network should be dealt with in a more effective way.
- Like GCN, GAT treat News-HIN as homogeneous network would be very disappointing.

Experiments
Evaluation Questions

- EQ1: Can AA-HGNN improve fake news detection performance by modeling data as a News-HIN?
- EQ2: Can Hierarchical Graph Attention (HGAT) mechanism handle the heterogeneity of the News-HIN effectively?
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Experiments

Methods performance on Heterogeneous graph

	Methods	PolitiFact Accuracy	PolitiFact Precision	PolitiFact Recall	PolitiFact F1	BuzzFeed Accuracy	BuzzFeed Precision	BuzzFeed Recall	BuzzFeed F1
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	AA-HGNN	**0.6155**	0.5661	**0.5804**	**0.5732**	**0.7351**	**0.7211**	**0.6909**	**0.7057**

- Beside the AA-HGNNs, HGAT achieves the best accuracy, recall and F1.
- GAT & GAN get high precision but low recall.
- Because they prefer to classify a sample as real news based on News-HIN, they were originally designed for homogeneous networks.
- HGAT can handle the heterogeneity of News-HIN well that HAN.

Experiments
Evaluation Questions

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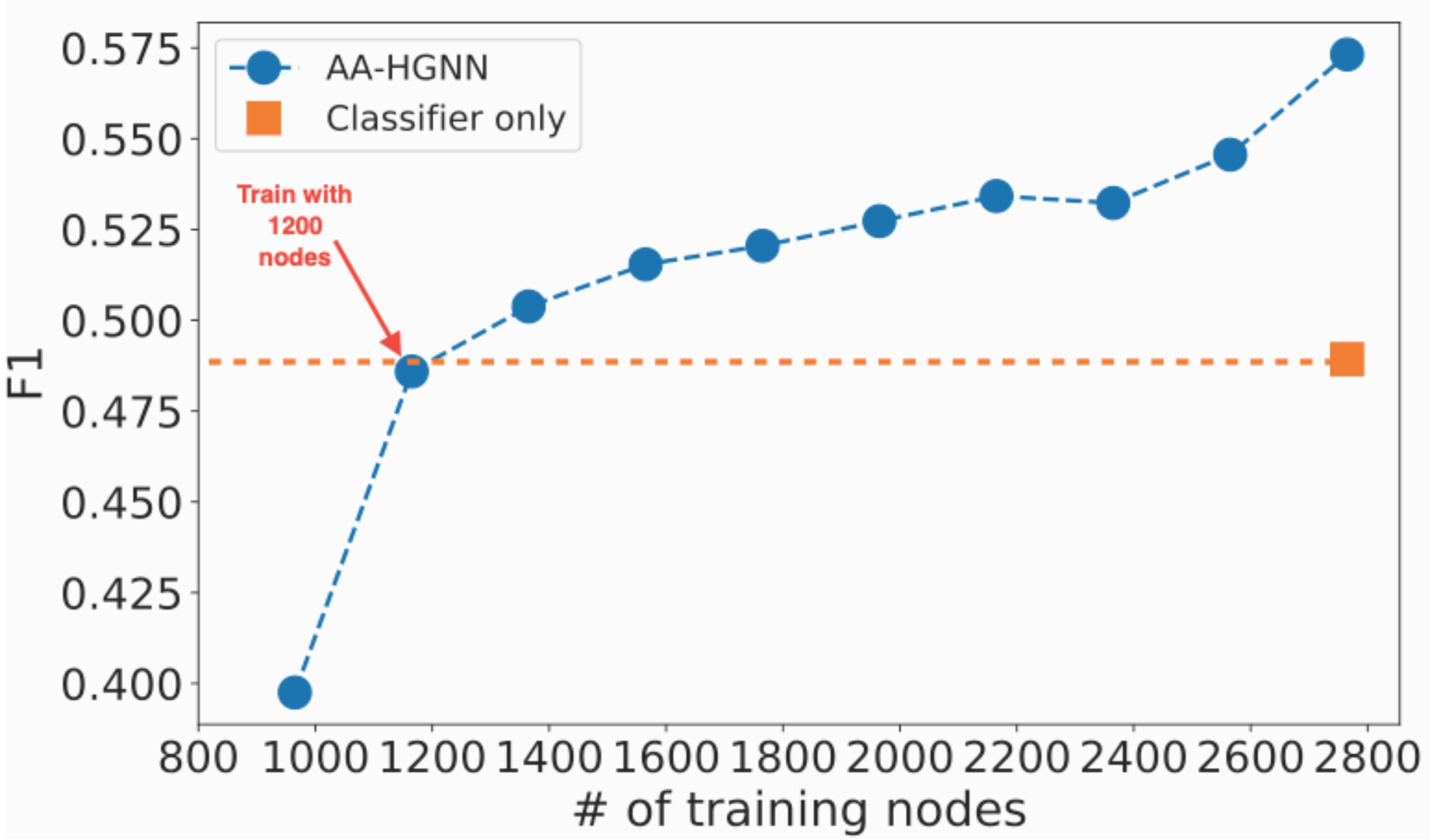
Experiments

Active learning setting on scarce training data

- AA-HGNN can outperform the classifier when being trained with 1200 labeled nodes.
- When the number of training nodes is 2800, the performance of AA-HGNN increase nearly 9% than the model without the active learning setting.
- Observe that AA-HGNN has the apparent advantage when using 20% training ratio, while other methods can not perform well due to the paucity of training data.
- AA-HGNN can reach satisfactory result although the training data is even more scarce.



	Number of training nodes									
Metrics	1000	1200	1400	1600	1800	2000	2200	2440	2600	2800
Accuracy	0.5658	0.5878	0.6049	0.6053	0.6013	0.5984	0.597	0.597	0.5955	0.6155
Precision	0.5142	0.5246	0.5218	0.5245	0.5135	0.5115	0.516	0.5136	0.5342	0.5661
Recall	0.3241	0.4526	0.4869	0.5065	0.5277	0.5441	0.5539	0.5523	0.5688	0.5804
F1	0.3975	0.4859	0.5038	0.5154	0.5205	0.5273	0.5342	0.5323	0.5456	0.5732

Experiments
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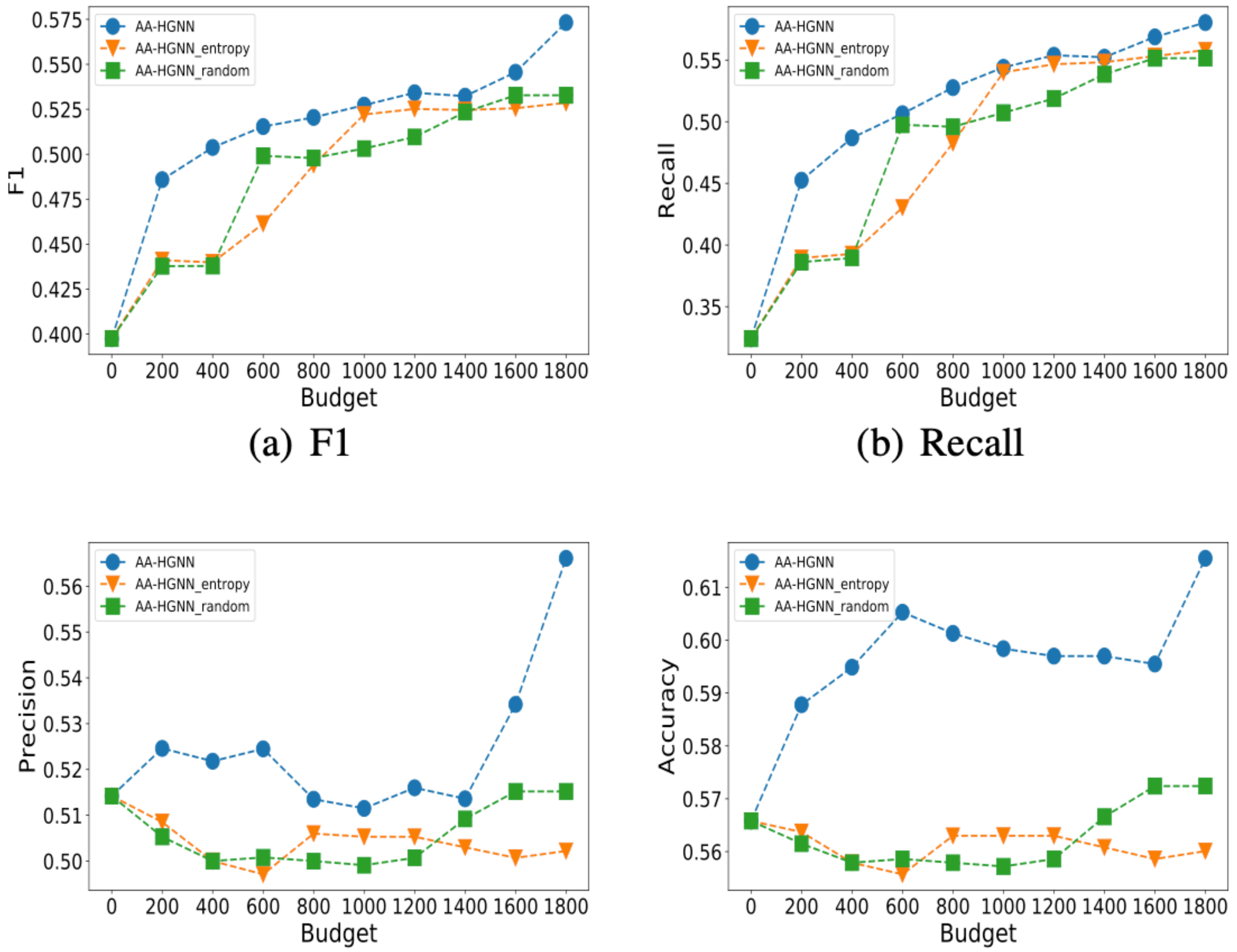
Experiments

Adversarial learning impacts on Active Learning

- AA-HGNN$_{entropy}$, AA-HGNN$_{random}$ provide different query strategies for active learning.
- Obvious that AA-HGNN outperform its variants in every query batch.
- Effective query strategy can consistently provide high-value candidates, as the performance of selectors also improves in adversarial learning.



(a) F1 (b) Recall

(c) Precision (d) Accuracy

Conclusion

- Study the HIN-based fake news detection problem and propose a novel adversarial active learning-based graph neural network AA-HGNN to solve it.
- AA-HGNN employs a novel hierarchical attention mechanism to deal with the heterogeneity of News-HIN and learns textual and structural information simultaneously.
- An active learning framework is applied in AA-HGNN to enhance the learning performance, especially when facing the paucity of labeled data.
- AA-HGNN is ideal for detecting fake news in the early stages when lacking training data and has good generalizability to widely used in other node classification-related applications.

Comments
of AA-HGNN

- Use HGAT hierarchical attention to get attention-based node representation.
- Use adversarial active learning (classifier, selector) to handle the paucity of labeled data problem.
- Proposed model can transfer to other HIN-base graph easily.
- The query strategy of selector is worth exploring. (select wrong answer to fix.)
- Only use textual content to extracted data representation.
- In Buzzfeed dataset, the article nodes is less.
- The comparison method is outdated ('14-'17).