

BotCourt: Towards Explainable Social Bot Detection via Collective Intelligence

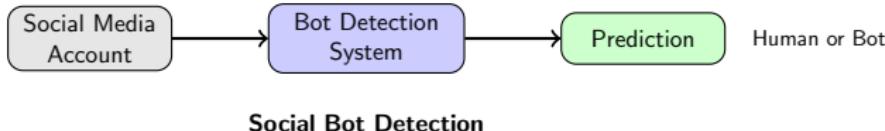
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Research Background

- ▶ Social bots pose significant threats to online social ecosystems
- ▶ Malicious purposes include:
 - ▶ Manipulating public discourse
 - ▶ Spreading disinformation
 - ▶ Interfering in elections and public health crises
- ▶ Need for social bot detection methodologies that are:
 - ▶ Accurate
 - ▶ Explainable
 - ▶ ...



Existing works for Social Bot Detection

- ▶ **Feature-based approaches**
 - ▶ User metadata
 - ▶ E.g., active days, follower/following count, posting frequency
- ▶ **Content-based approaches**
 - ▶ User text
 - ▶ E.g., tweet content, description, name
- ▶ **Graph-based approaches**
 - ▶ Social structure, including user metadata, text, and neighbors
 - ▶ Graph node (embedding based on metadata/text/...)
 - ▶ Graph edge (relation based on follower/following/...)

Challenges and Opportunities

► Insufficient Explainability:

- ▶ Existing methods focus on accuracy and often fail to provide explanations for predictions [1]
- ▶ Such as confidence or evidence for the decision

► Threats Posed by LLM:

- ▶ Social bots powered by LLM are more difficult to distinguish from human accounts in terms of content [2, 3]
- ▶ Increasing the decision-making risk of detection systems

► Opportunities for LLM-based approaches:

- ▶ LLMs are trained on lots of data, which can provide rich knowledge for social media bot detection
- ▶ LLMs can be used to provide explanations for decision-making, which is more interpretable for humans

Preliminary Experiment: LLM for Bot Detection

Key Insights: The LLMs without fine-tuning showed competitive results compared to supervised learning baselines on the Twibot-22 dataset [4].

Model	Approach	Acc.	F1	Prec.	Rec.
SGBot BOTPERCENT ROBERTA BOTOMETER BOTBUSTER LOBO RGT	Baseline	0.623	0.395	1.000	0.247
		<u>0.731</u>	0.726	0.738	0.714
		0.633	0.432	0.955	0.280
		0.755	0.585	0.440	0.873
		0.627	<u>0.439</u>	0.882	0.292
		0.552	0.198	0.944	0.110
Gemma-7b	tweet	0.515	0.525	0.514	0.535
	metadata	0.444	0.415	0.438	0.394
	description	0.521	0.519	0.521	0.518
	meta + desc	0.509	0.480	0.510	0.453
	structure	0.559	0.556	0.560	0.553
Mistral-v0.1-7b	tweet	0.447	0.580	0.468	0.765
	metadata	0.497	0.190	0.488	0.118
	description	0.521	0.546	0.519	0.577
	meta + desc	0.409	0.236	0.333	0.182
	structure	0.547	0.267	0.700	0.165
Mistral-v0.3-7b	tweet	0.553	0.487	0.571	0.424
	metadata	0.644	0.686	0.614	0.777
	description	0.485	0.249	0.460	0.171
	meta + desc	0.668	0.700	0.638	0.777
	structure	0.538	0.511	0.543	0.482
Qwen2.5-7b	tweet	0.532	0.413	0.555	0.329
	metadata	0.650	0.659	0.643	0.677
	description	0.677	0.686	0.667	0.706
	meta + desc	0.656	0.686	0.631	0.753
	structure	0.621	0.706	0.576	0.912

Bold: max value in Baseline; Underline: 2nd max value in Baseline.

Red: max value among four LLMs; **Blue:** 2nd max value among four LLMs;

Motivations

Core Idea: For social platforms, a social bot detection system should be an explainable decision-making support tool rather than a black box that can only output prediction results.

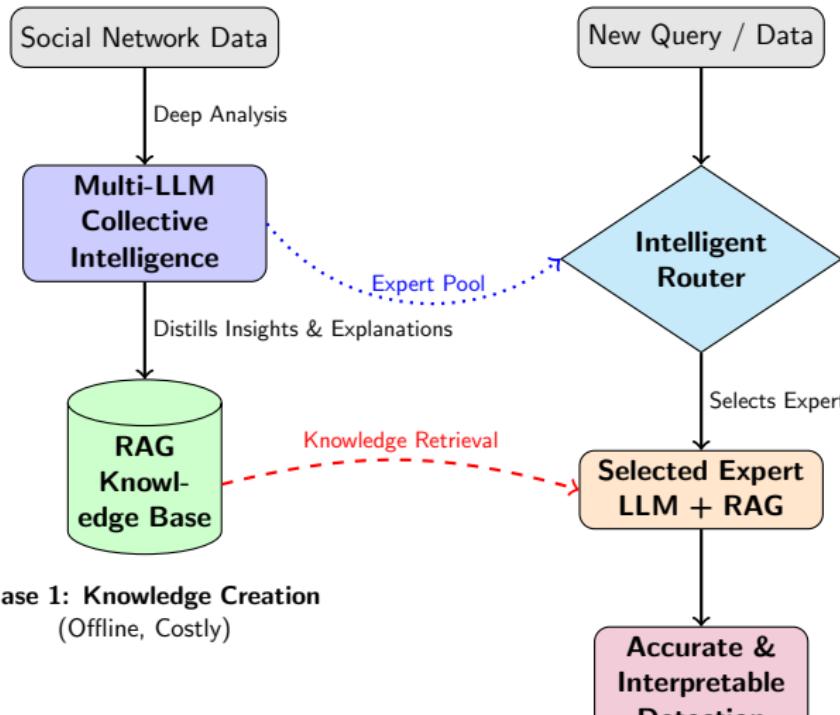
1. Collective Intelligence for Interpretable Evidence Mining

- ▶ Leverages a multi-LLM system where LLMs debate and review to dissect sophisticated bot behaviors [5, 6].
- ▶ Delivers high-quality, human-readable explanations for each detection, transforming the decision-making black box into an interpretable reasoning process.

2. Adaptive Inference via Expert Routing and RAG

- ▶ Implements an intelligent router to select the optimal expert LLM from the multi-LLM system based on the input sample.
- ▶ The selected expert then performs RAG-augmented inference [4], retrieving tailored reasoning patterns to ensure high accuracy and interpretability.

Proposed Framework



Core: Multi-LLM Collective Intelligence

Question: How to leverage collective intelligence for detection?

Answer: LLM-as-a-judge, Propose → Rebuttal → Judge

Plan 1: Multi-LLM System [5]

- ▶ **Multiple specialized LLMs**
 - ▶ Each LLM has a distinct perspective/knowledge
 - ▶ E.g., different LLM, different pretrained dataset
- ▶ **Collective decision-making**
 - ▶ Multi-LLM debate and review mechanism

Plan 2: Single LLM with Multiple Roles [7]

- ▶ **Single LLM with role-playing**
 - ▶ Same LLM, different role-based prompts
 - ▶ E.g., proposer, rebutter, judge roles
- ▶ **Virtual multi-llm debate**
 - ▶ Role-based single-LLM debate and review

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