



**ISCram 2025**

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MAY 18-21

# Dynamic Fusion of Large Language Models for Crisis Communication

Xiaoying Song, Anirban Saha Anik, Vanessa Frías-Martínez, Lingzi Hong



UNIVERSITY OF  
MARYLAND

Work-in-Progress Paper

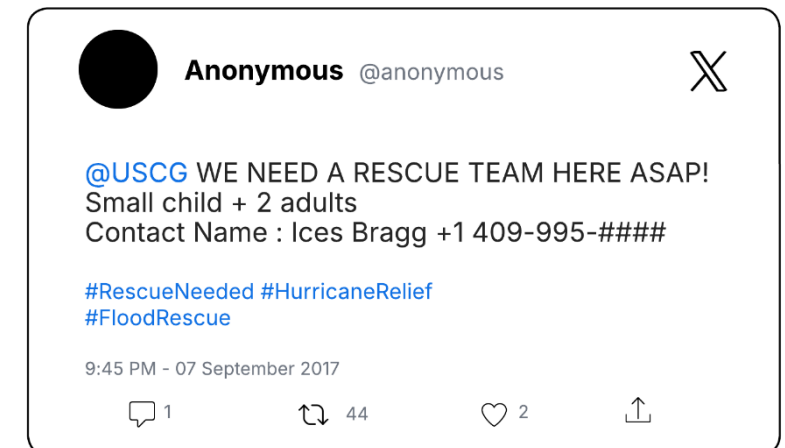
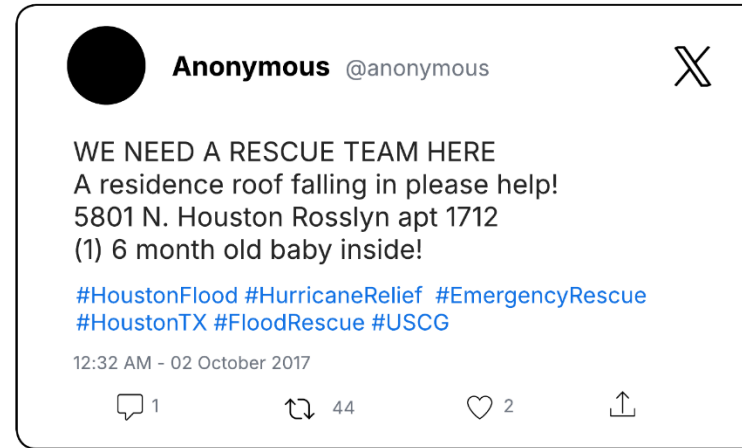
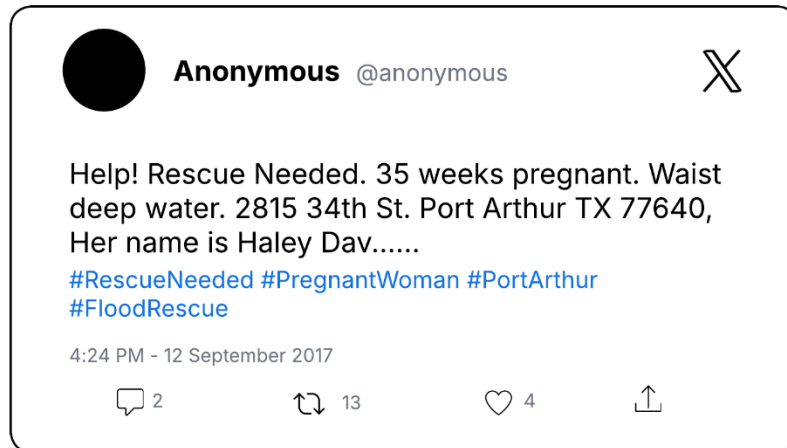
Presented By Anirban Saha Anik

# Outline

- Motivation
- Research Question
- Methods
- Results
- Takeaways

# Motivation & Problem

“Real help requests posted during Hurricane Irma on Twitter (X)”

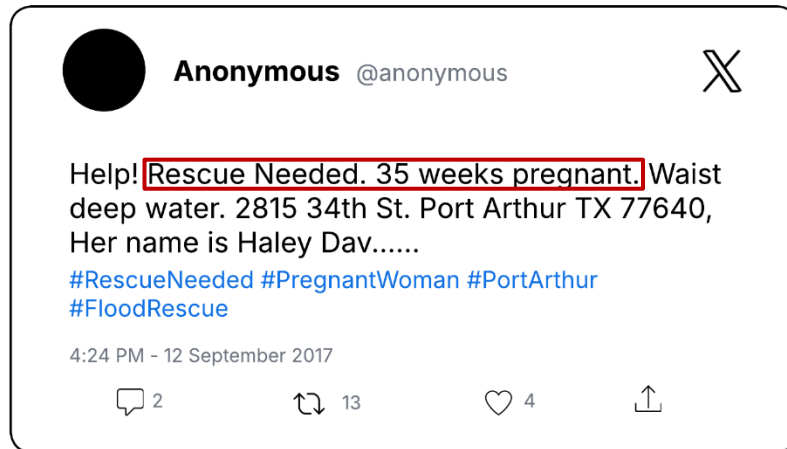


**Source:** Hurricane Irma Tweets (Hong et al. 2020)

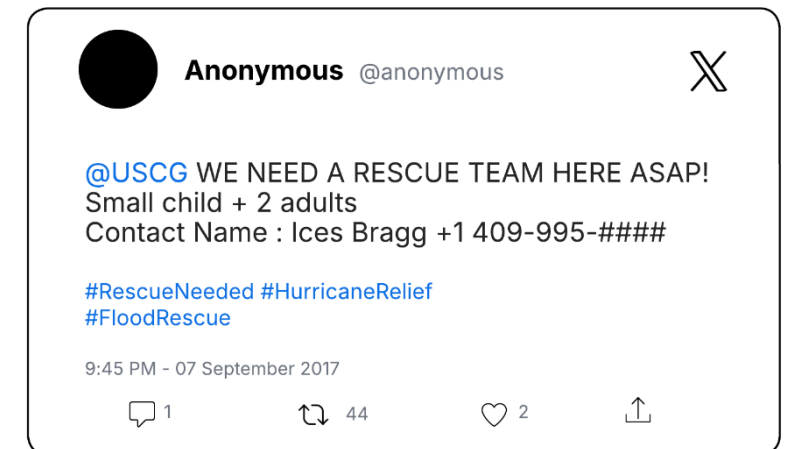
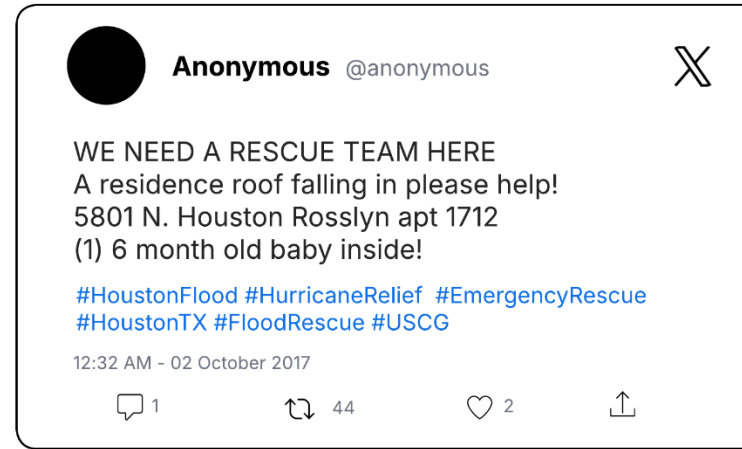
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Medical Emergency

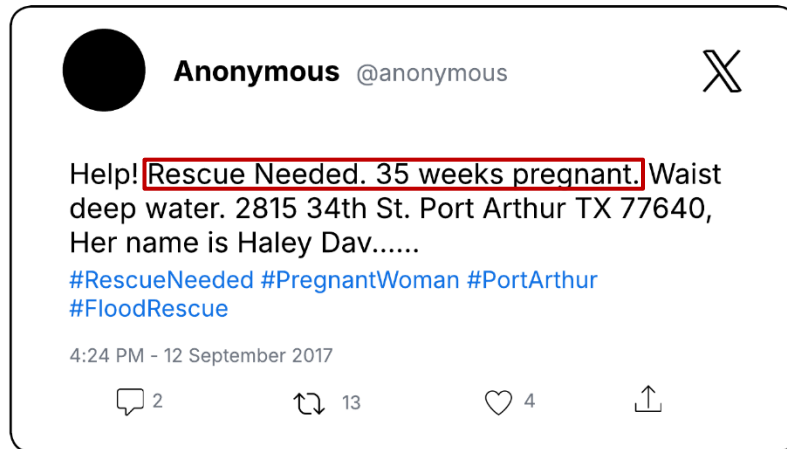


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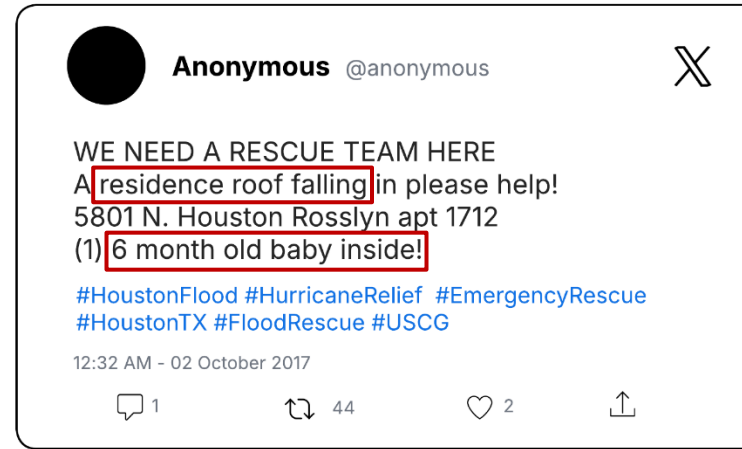
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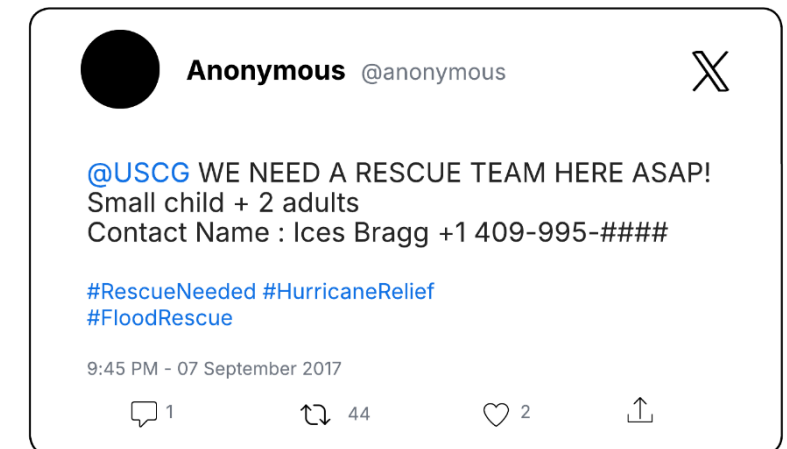
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Structural Collapse

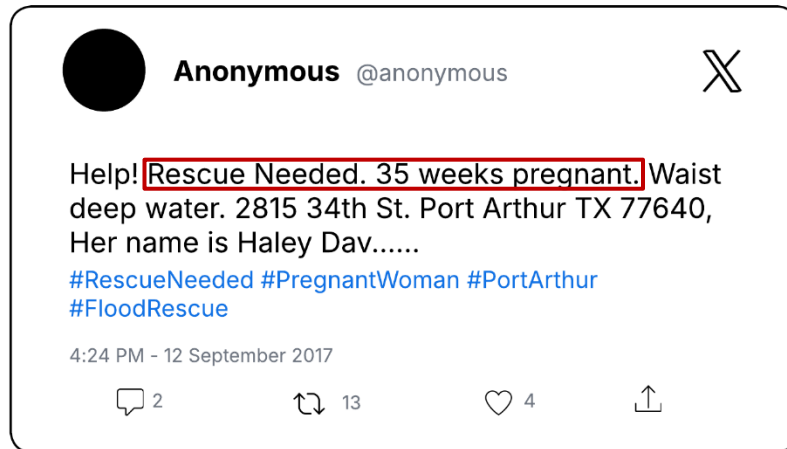


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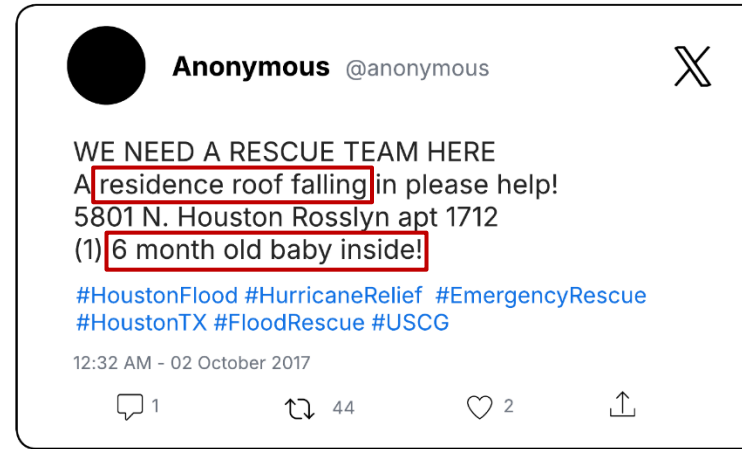
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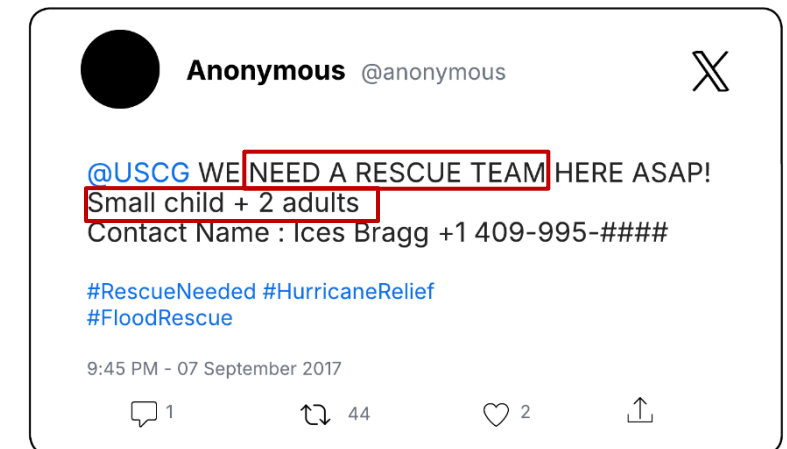
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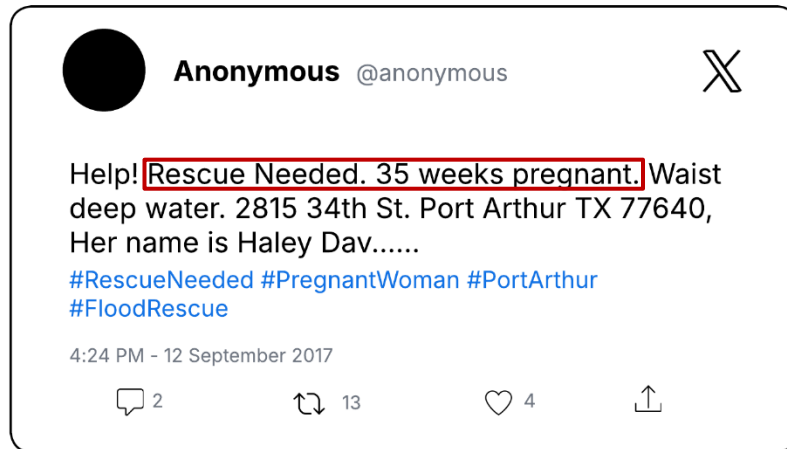
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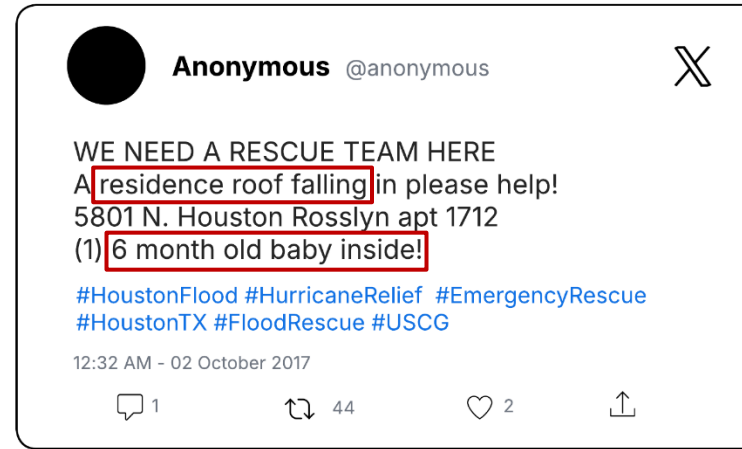
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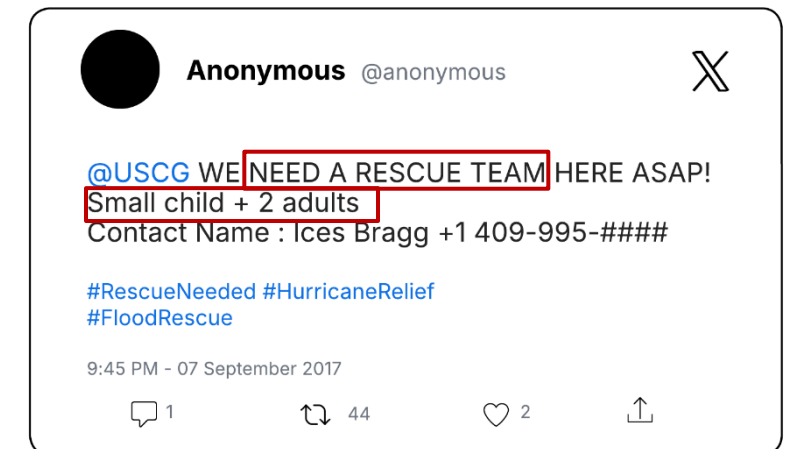
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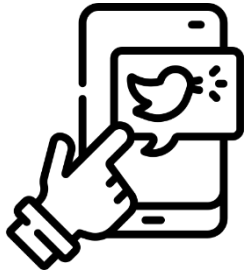
*“Thousands of people post help requests like these—but many receive no response.”*

Source: Hurricane Irma Tweets (Hong et al. 2020)

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# During Disasters, People Turn to Social Media for Help...

- People post urgent needs on Twitter (X), hoping someone will respond.

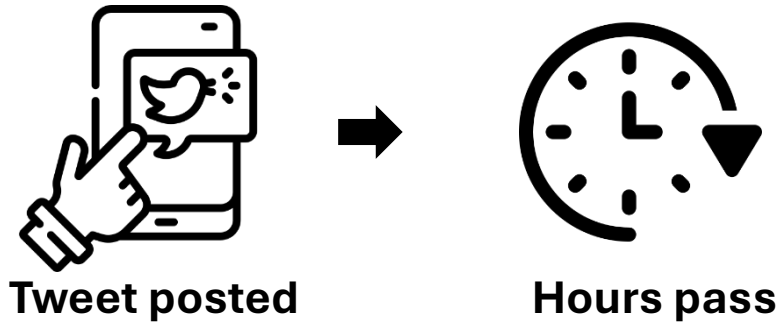


**Tweet posted**



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**What if AI could step in and help respond—fast, helpful, and reliable?**

# Our Goal

## Main Objective

Build an AI assistant that can generate fast, helpful, and human-like responses to crisis-related social media posts.



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## What We Aim to Achieve

- **Understand the help-seeker's intent** from short, noisy tweets
- **Provide factually accurate and grounded information** using trusted sources
- **Deliver clear, actionable steps** people can follow during an emergency
- **Show empathy** to build trust and provide emotional support
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## Our Approach

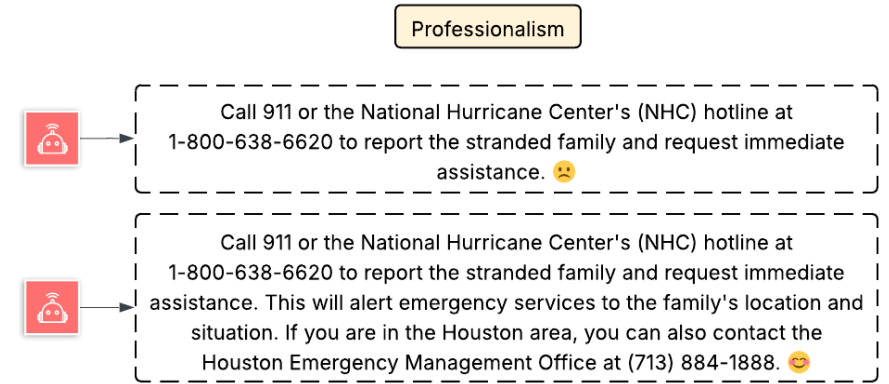
We explore **three methods** using Large Language Models (LLMs):

1. **Instruction Prompt** – guided generation
2. **RAG** – Document-grounded generation
3. **Dynamic Fusion** – *Our proposed method to combine the best of both*



# Evaluation Dimensions

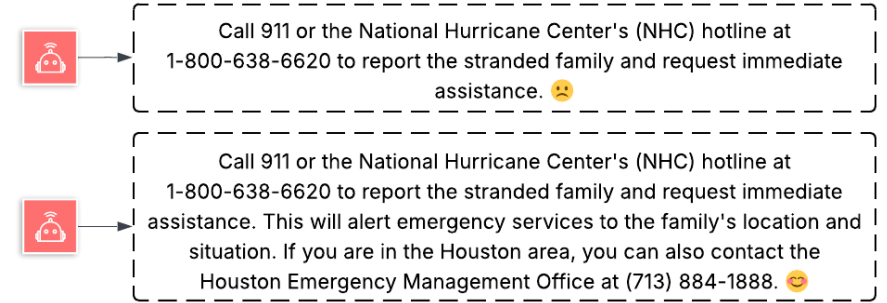
- **Professionalism** – The response sounds official, reliable, and well-informed.



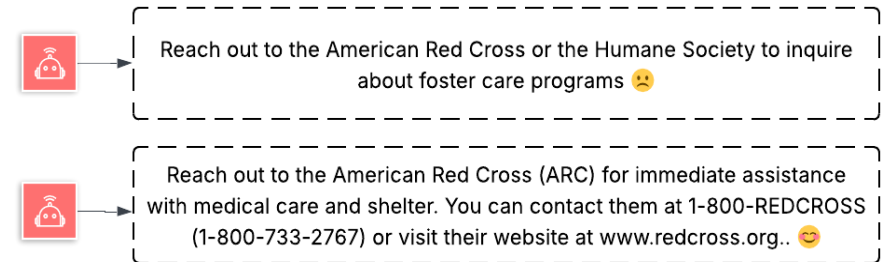
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## Professionalism



## Actionability

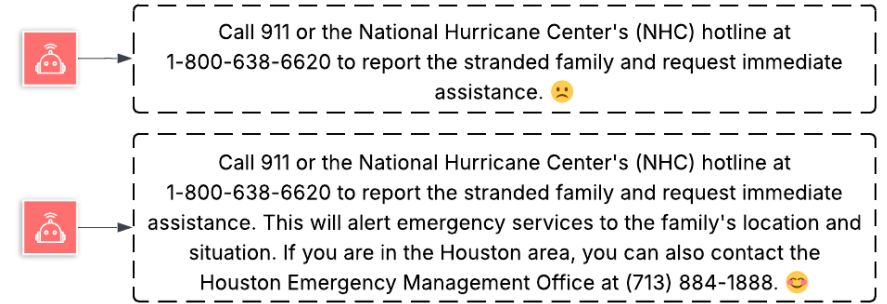




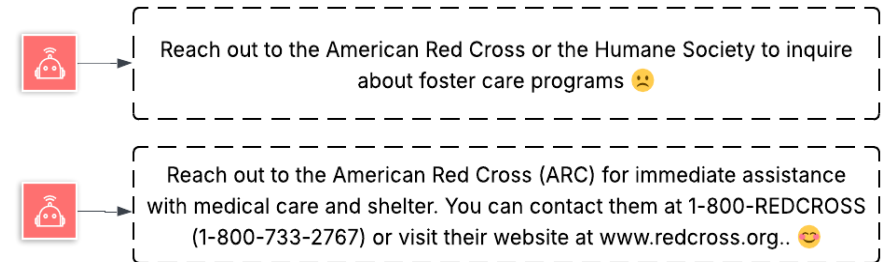
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- **Professionalism** – The response sounds official, reliable, and well-informed.
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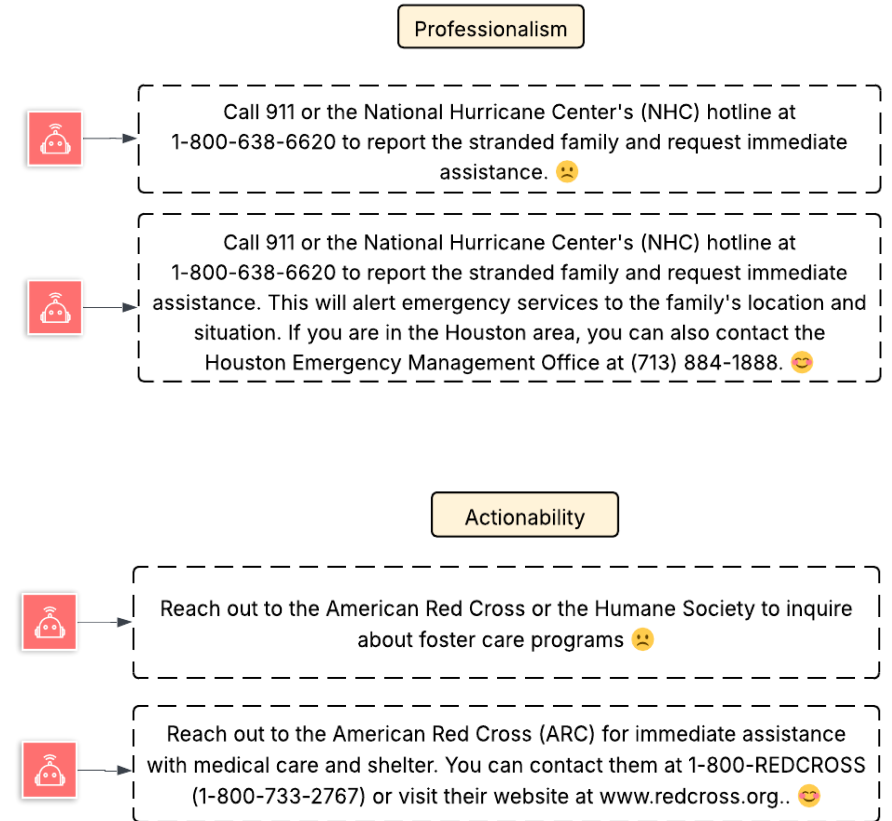


## Actionability



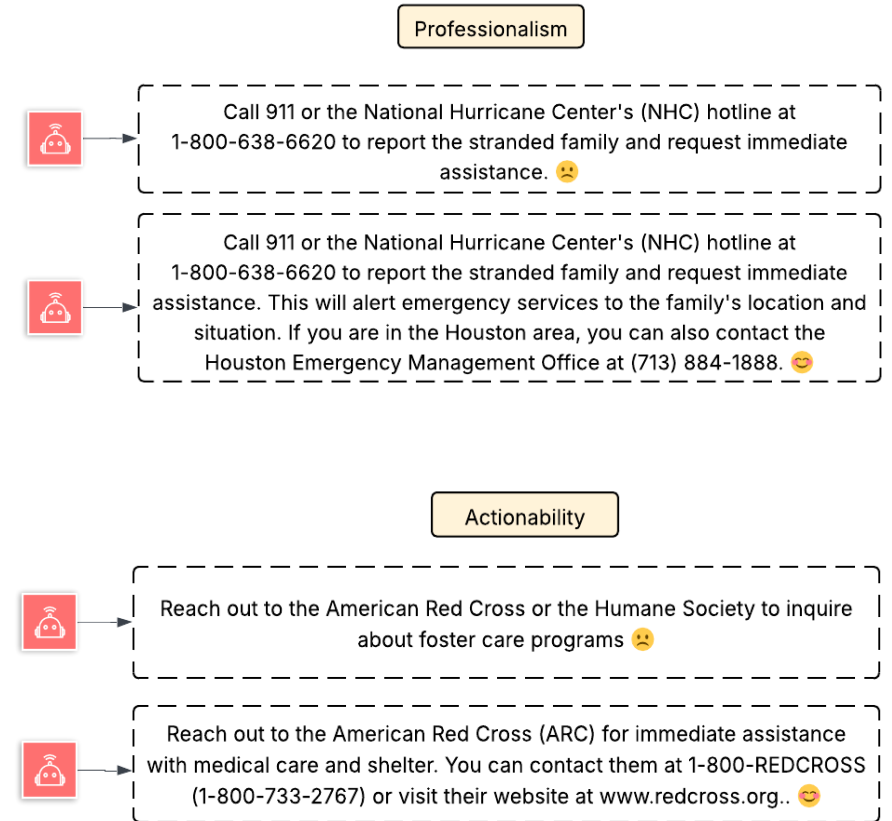
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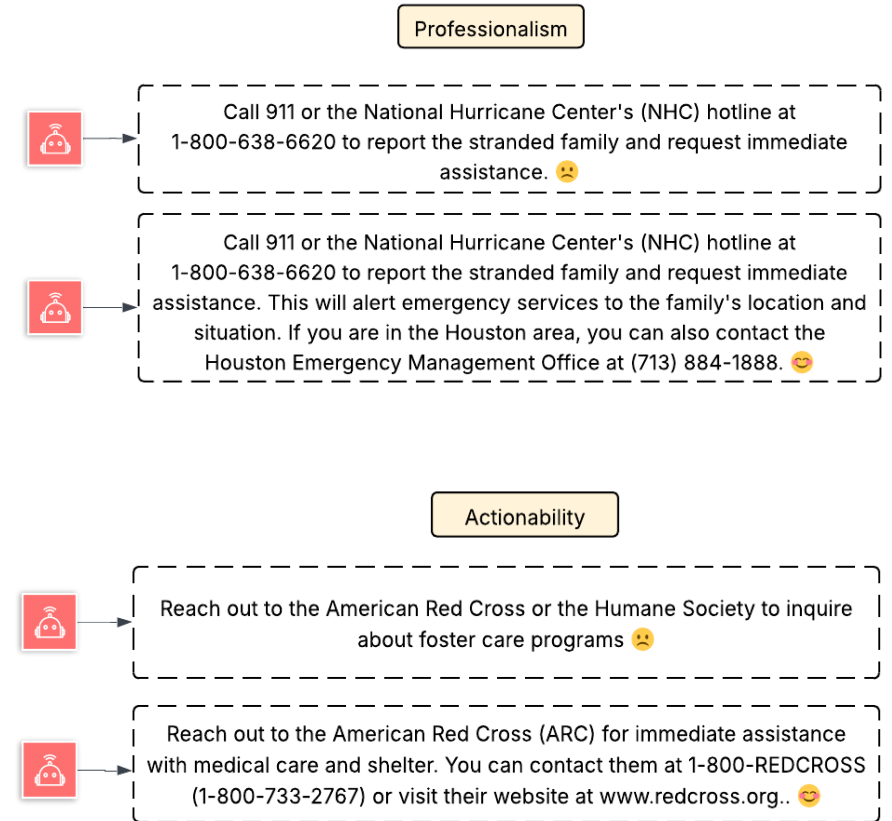
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- **Overall Quality Score** – We calculate a weighted score  
 $Q = 0.4 \times \text{Professionalism} + 0.4 \times \text{Actionability} + 0.1 \times \text{Empathy} + 0.1 \times \text{Relevance}$



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*“Good crisis communication must be clear, credible, caring, and on point.”*

# Dataset

## Raw Dataset

- **Source:** Hurricane Irma Tweets (*Hong et al. 2020*)<sup>1</sup>
- **Timeframe:** August 15 – October 12, 2017
- **Location:** 6 Southern U.S. states  
(*Florida, Georgia, South Carolina, North Carolina, Tennessee, Alabama*)
- **Raw Data:** 1,013,313 tweets from 127,181 users



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## Detecting Needs-Related Tweets

- Trained **three RoBERTa models** on crisis-labeled datasets (*Alam et al., 2021a; Alam et al., 2021b*)<sup>2,3</sup>
  - HumanAID, CrisisBench, Turkey Earthquake Relief
- Tweets labeled as **"needs-related"** if all three models agree



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## Final Labeled Dataset

- **540 verified needs-related tweets**
- Used as input for LLM-based response generation



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## What is Instruction Prompting?

Give an LLM clear, structured instructions to generate a response for crisis-related tweets.

## Prompt Design

You are an AI assistant designed to provide professional, actionable, empathetic, and relevant advice for someone seeking help related to a hurricane on social media.

Given the following tweet expressing needs during a hurricane, provide a detailed solution. If you don't know the answer, clearly state, "I don't know".

### Guidelines:

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## How It Works – 3 Steps

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  - Split into small chunks for retrieval.



Knowledge Base

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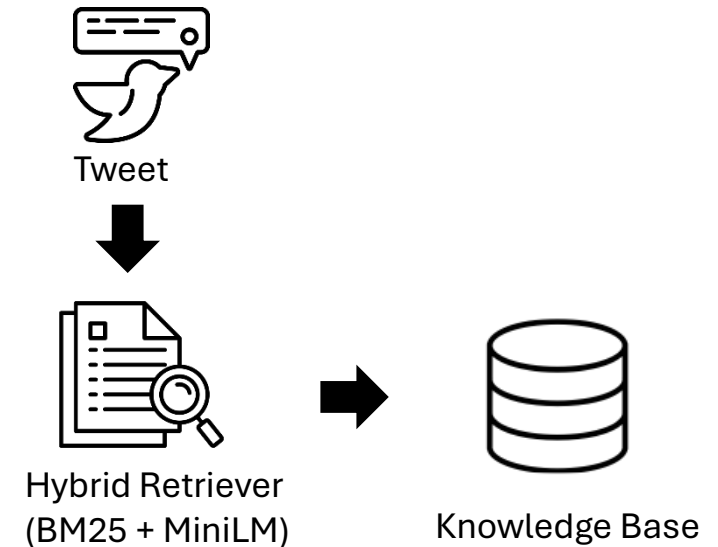
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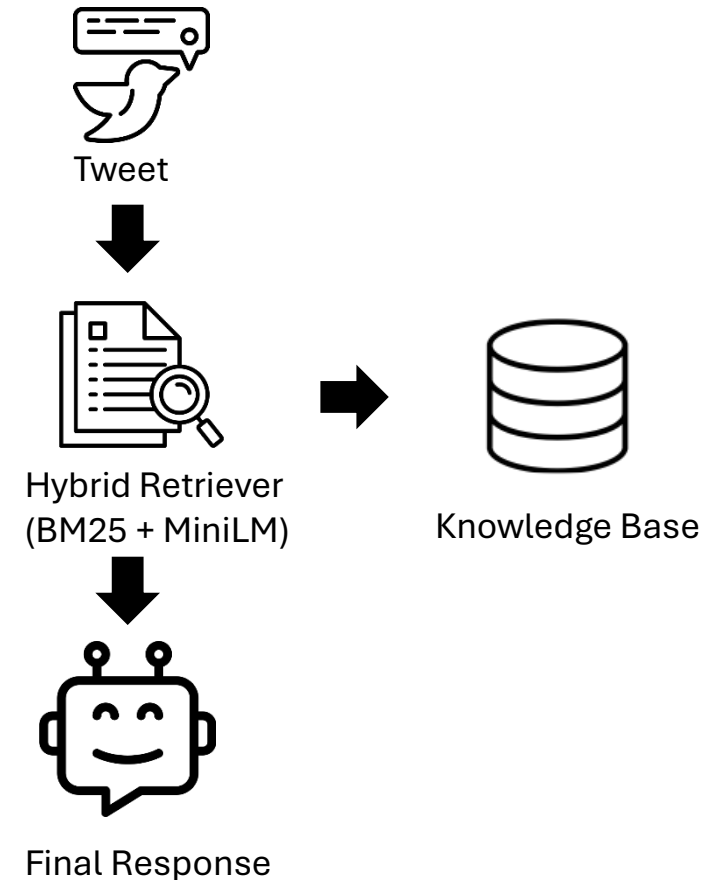
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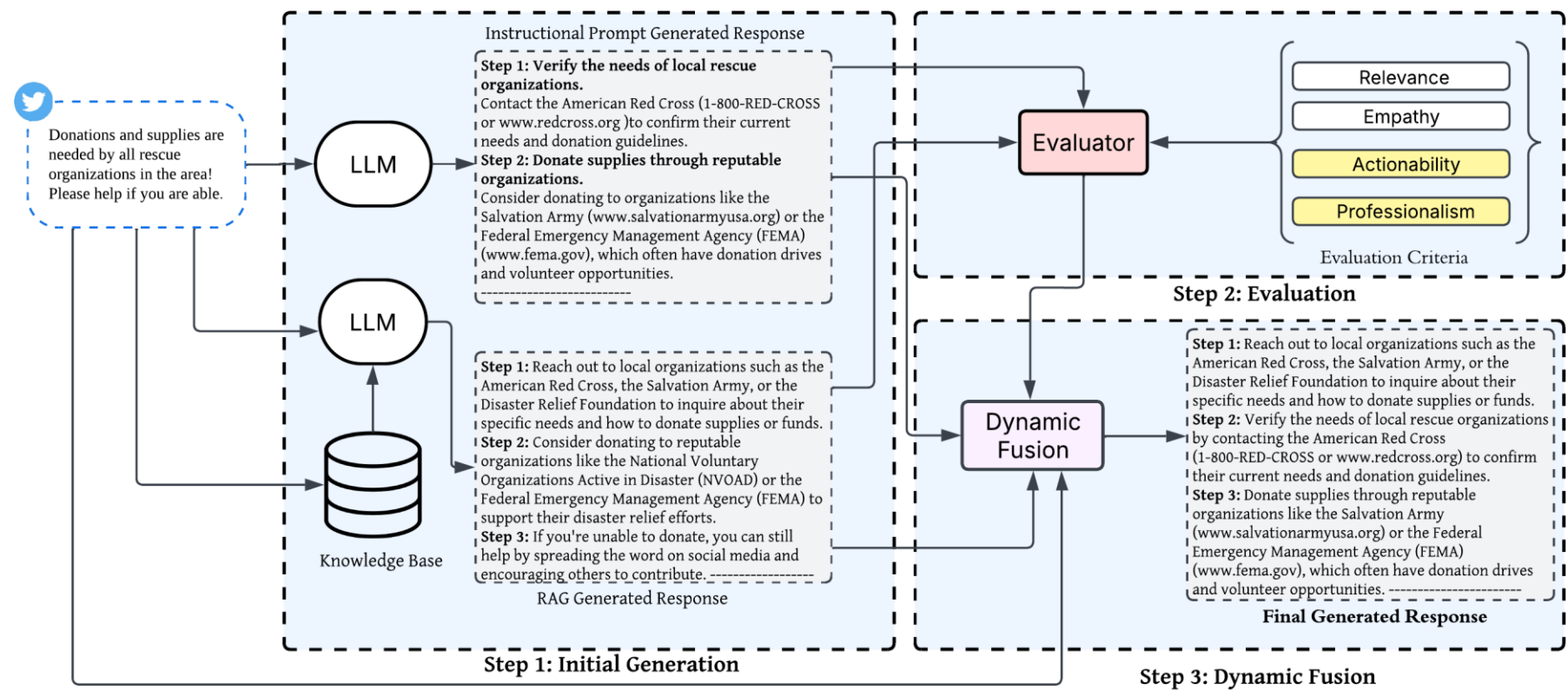
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  - Top-5 relevant documents selected.
- **Response Generation**
  - The retrieved documents are **concatenated with the user tweet** and fed into the LLM.
  - Generates a grounded, informative reply.

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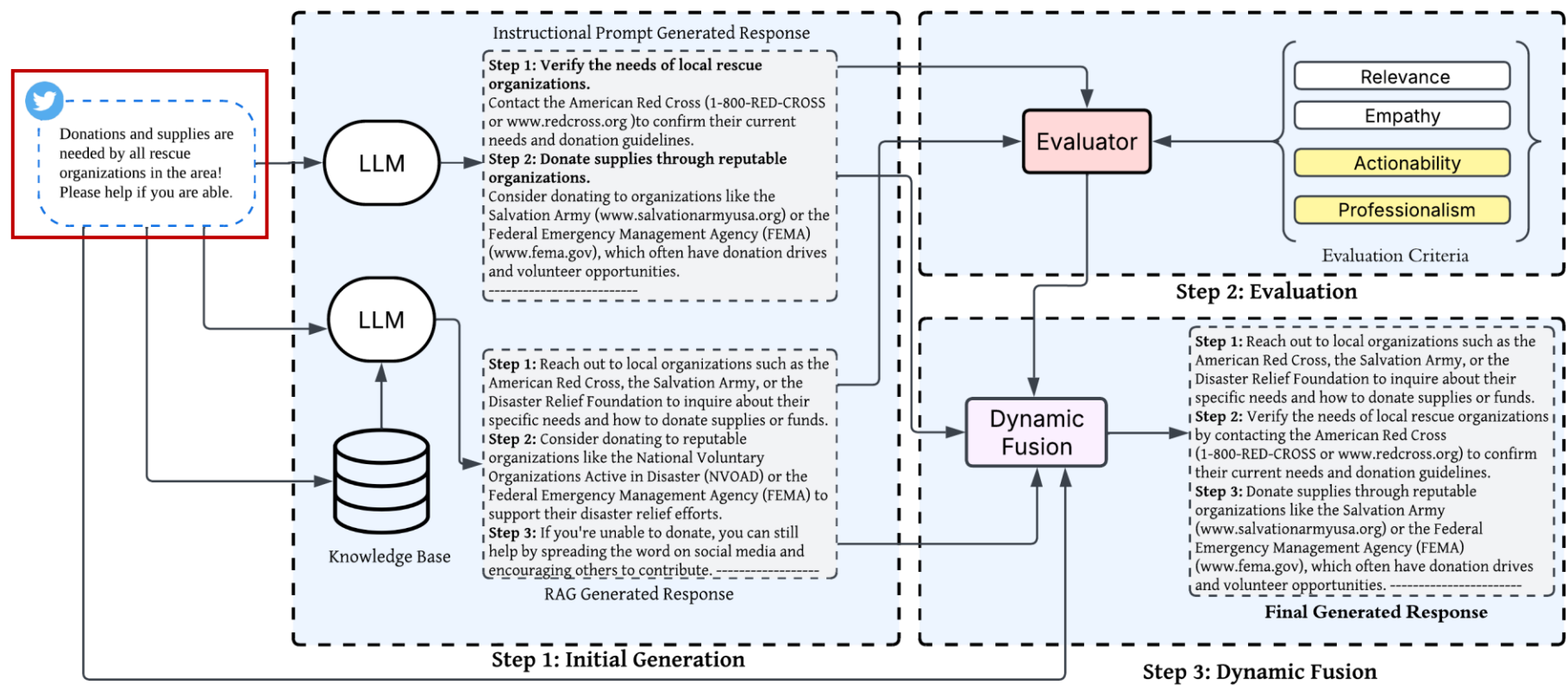


# Dynamic Fusion (Our Contribution)

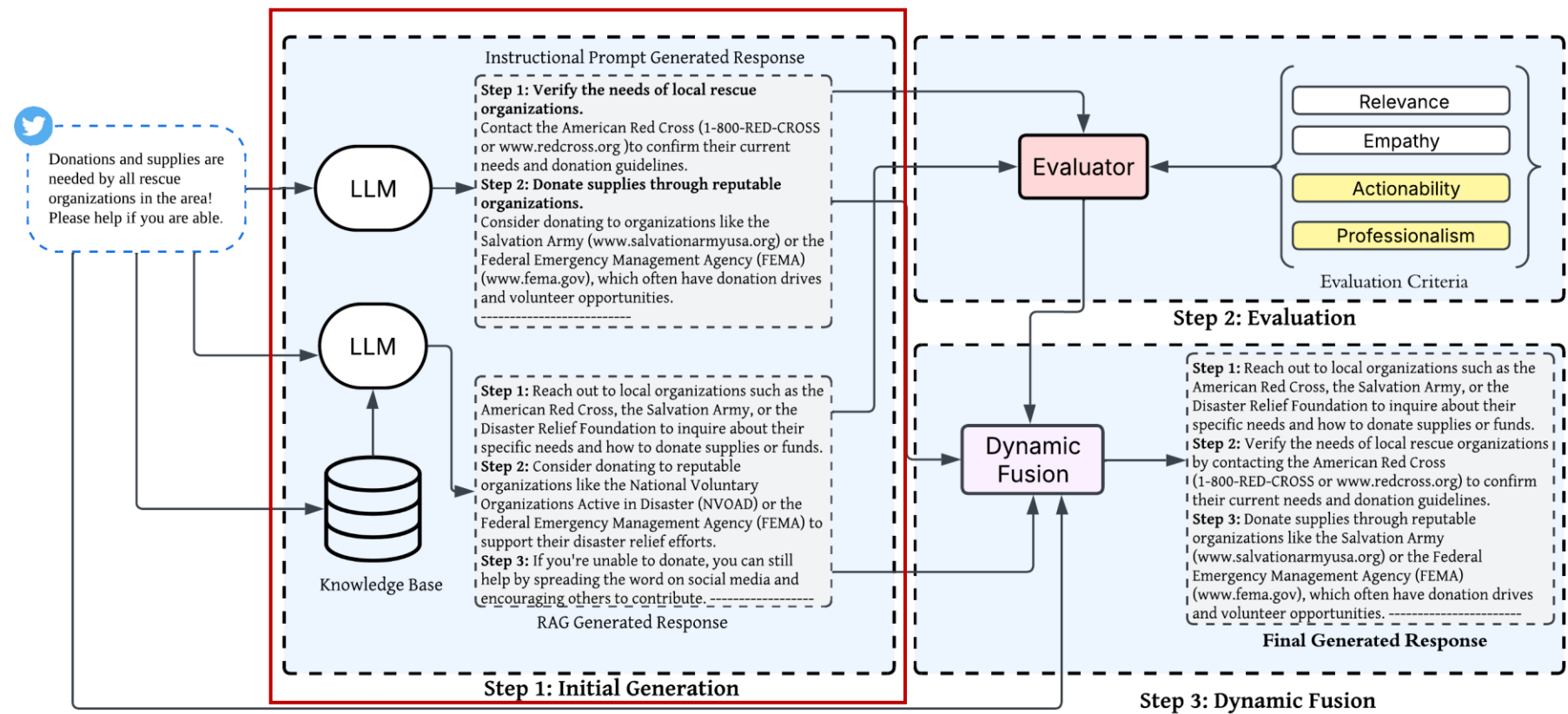




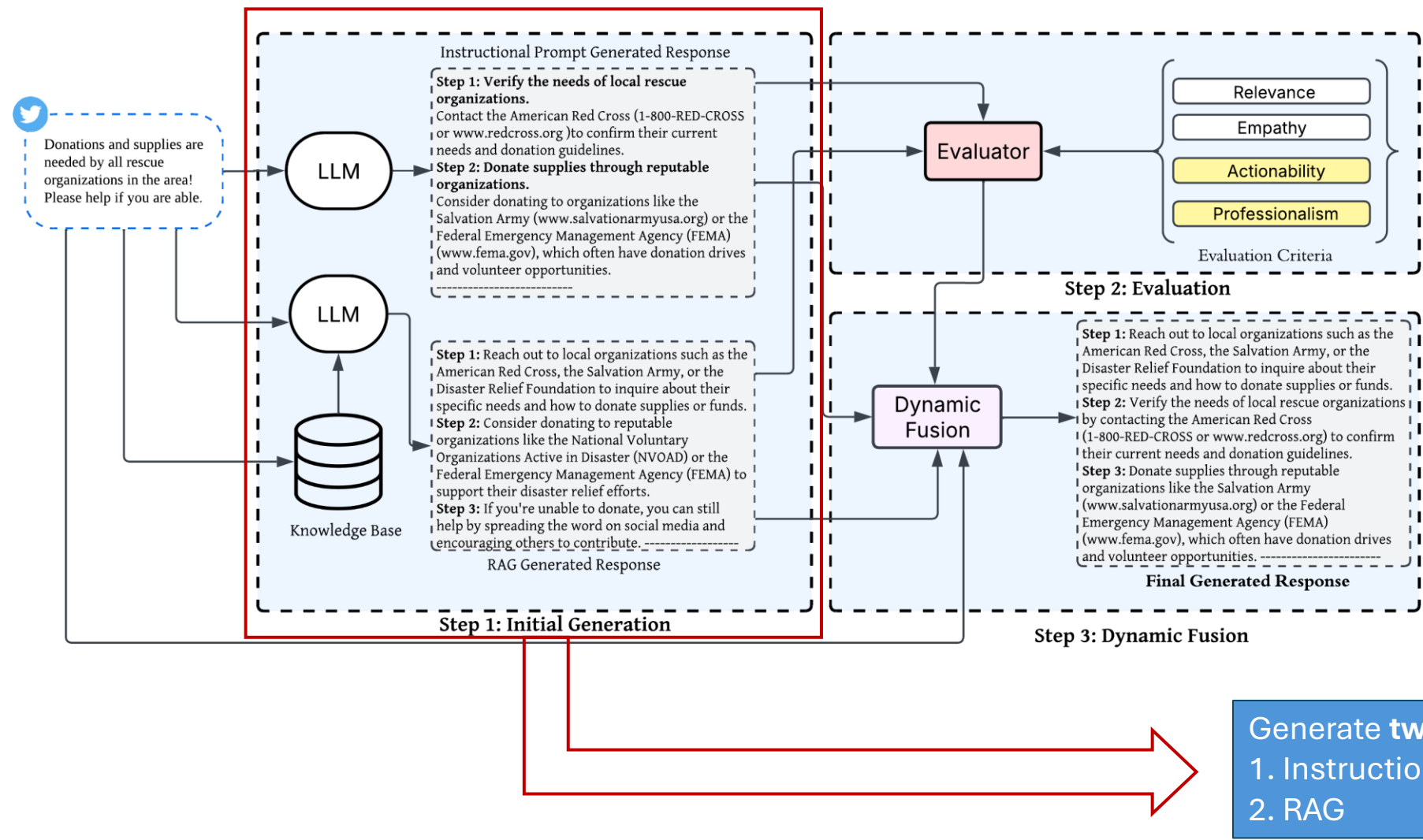
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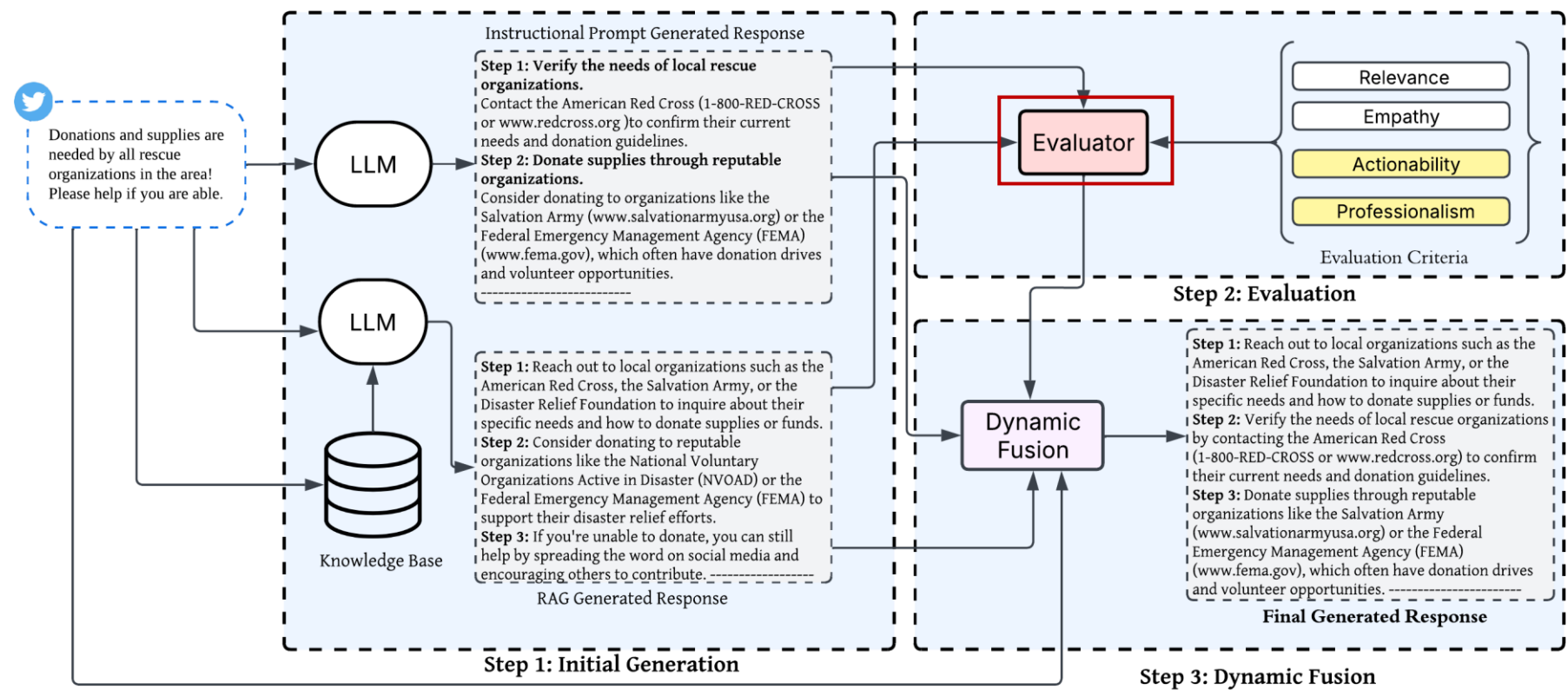
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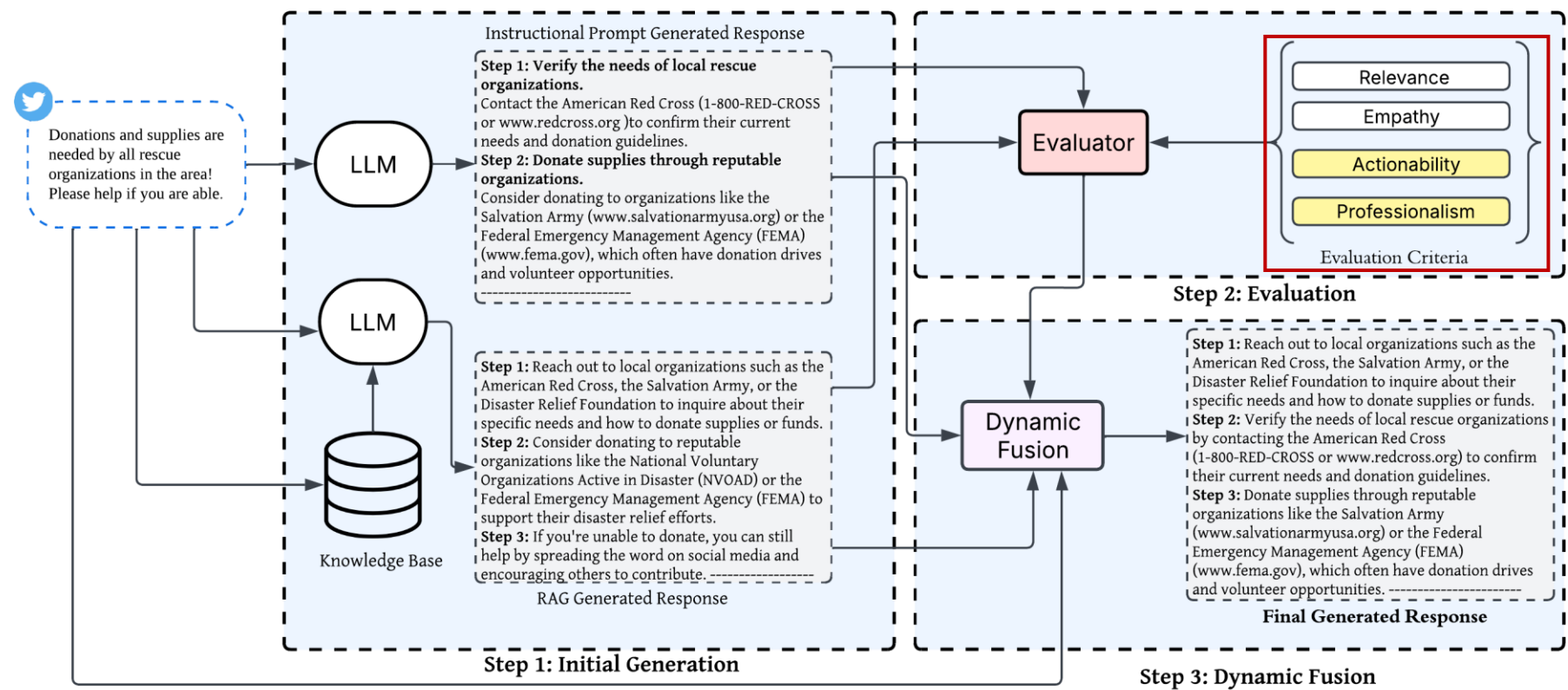
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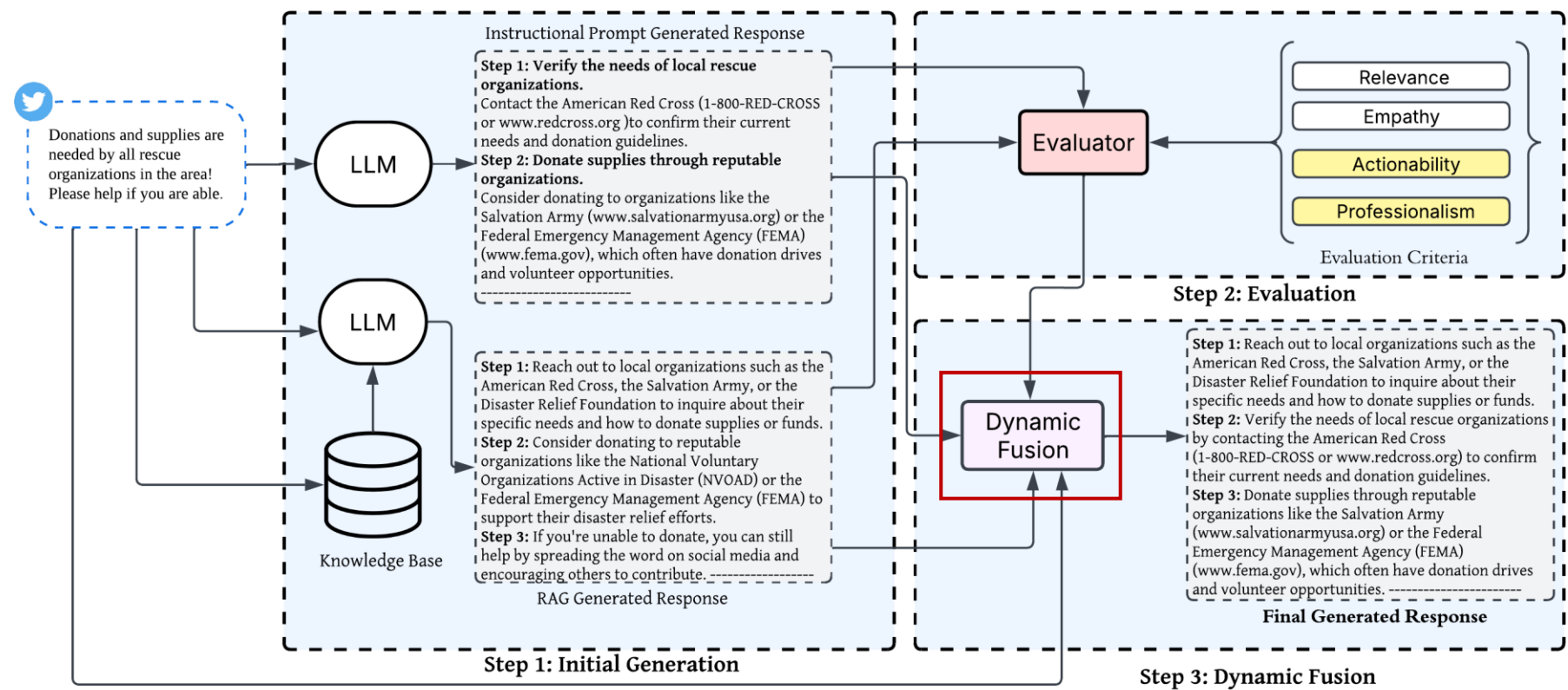
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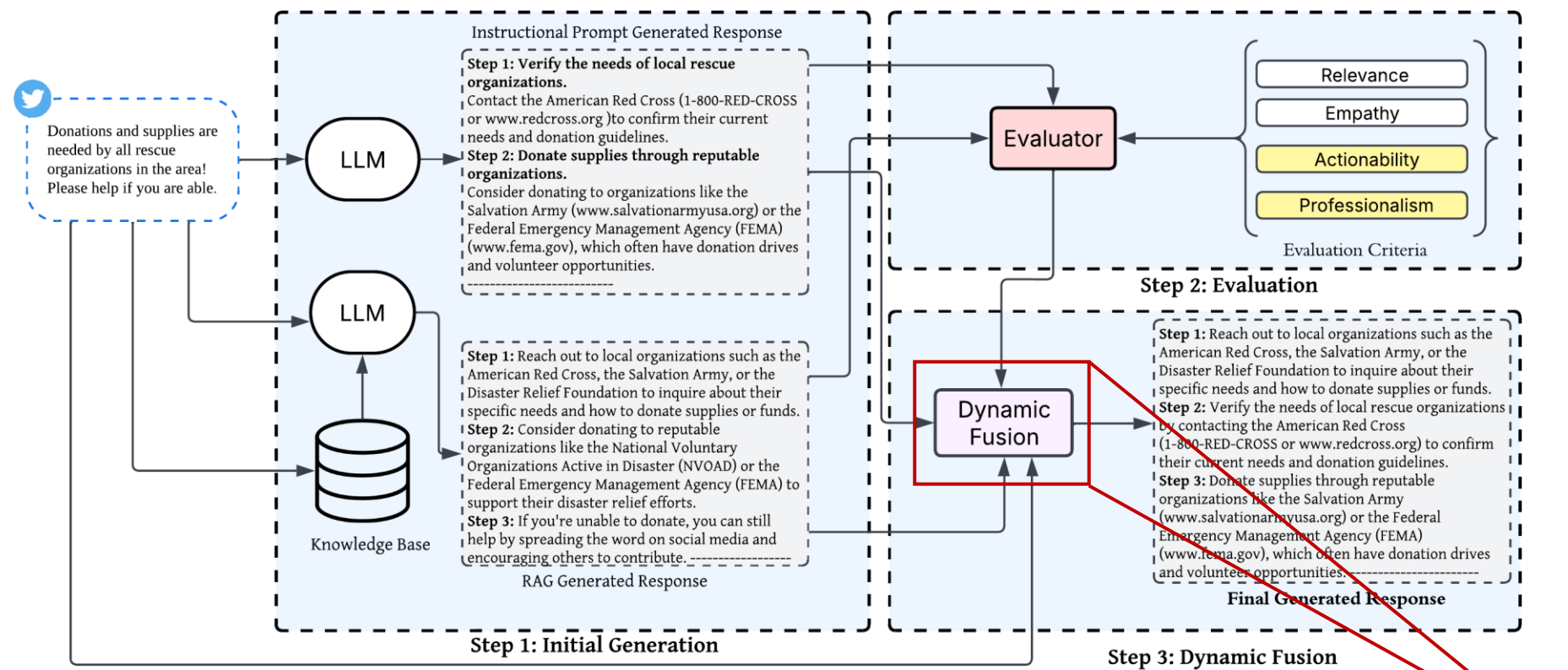


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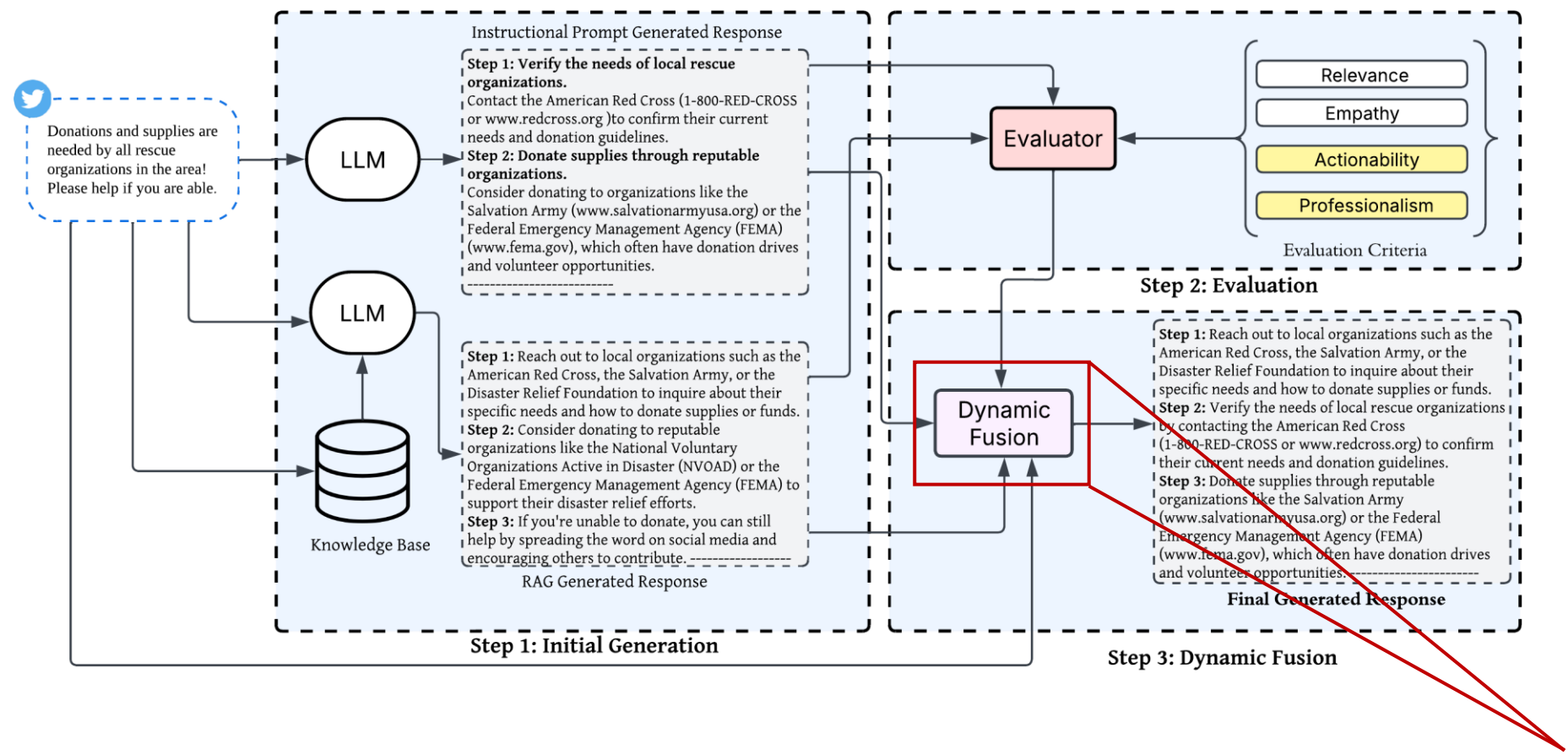


# Dynamic Fusion (Our Contribution)



If one response scores highest across all → **Select it**

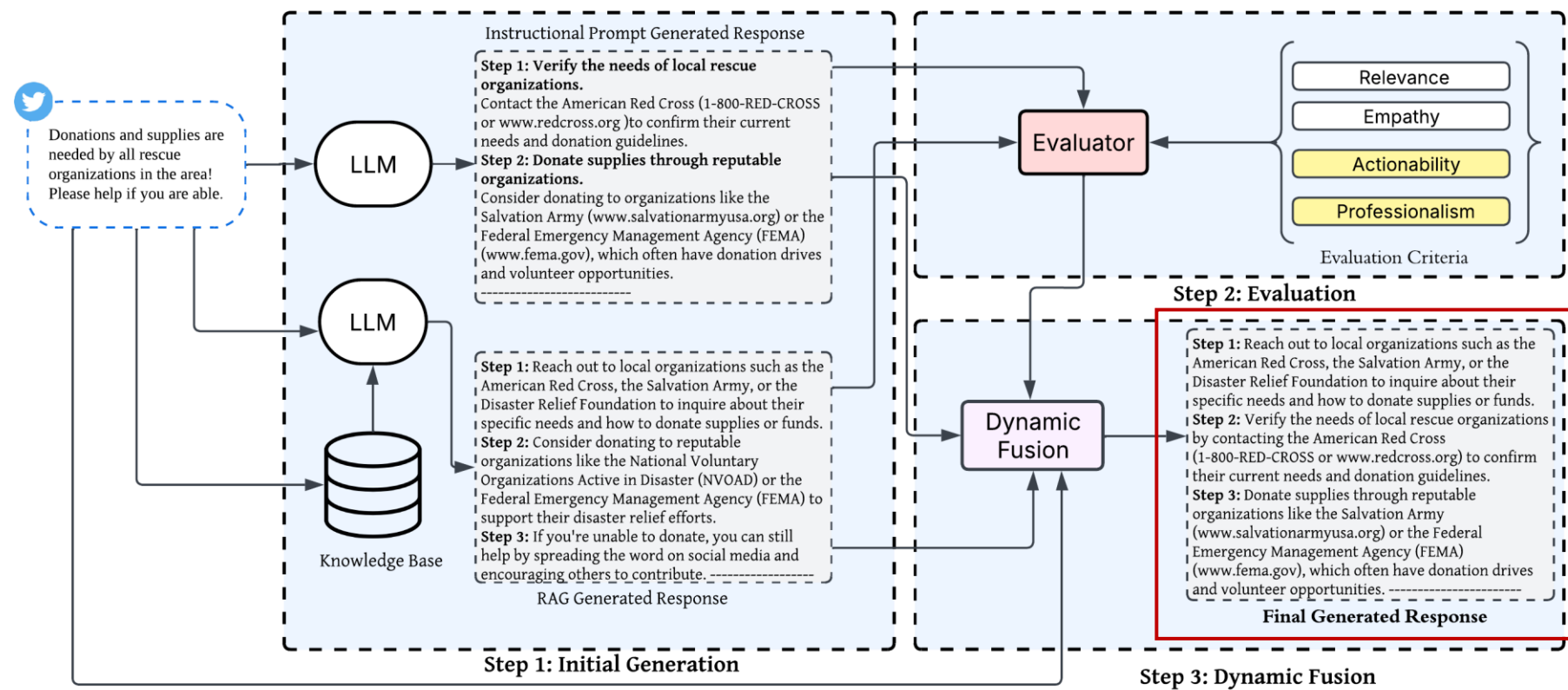
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If mixed performance → **Fuse** the best-scoring parts from each



# Dynamic Fusion (Our Contribution)



# Results

## How Well Do the Methods Perform?

We evaluate responses generated by:

- **Instruction Prompt**
- **Retrieval-Augmented Generation (RAG)**
- **Dynamic Fusion (Proposed)**

Across three LLMs:

- LLaMA 3.1 8B Instruct
- Mistral 8B Instruct
- Qwen2.5 7B Instruct

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Model	Method	P	A	E	R	O (Overall)
LLaMA	Instruction Prompt	0.74	0.52	0.06	0.43	0.55
	RAG	0.96	0.63	<b>0.22</b>	0.40	0.70
	<b>Dynamic Fusion</b>	<b>0.92</b>	<b>0.97</b>	0.04	<b>0.46</b>	<b>0.81</b>
Mistral	Instruction Prompt	0.87	0.98	0.03	0.41	0.78
	RAG	0.87	0.97	0.13	0.42	0.79
	<b>Dynamic Fusion</b>	<b>0.97</b>	<b>0.99</b>	0.06	<b>0.50</b>	<b>0.84</b>
Qwen	Instruction Prompt	0.98	0.99	0.03	0.45	0.84
	RAG	0.79	0.86	<b>0.14</b>	0.47	0.72
	<b>Dynamic Fusion</b>	<b>0.98</b>	<b>0.99</b>	0.08	<b>0.51</b>	<b>0.85</b>

**P** = Professionalism; **A** = Actionability; **E** = Empathy; **R** = Relevance; **O** = Overall Quality (weighted).

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	Dynamic Fusion	<b>0.92</b>	<b>0.97</b>	0.04	<b>0.46</b>	<b>0.81</b>
Mistral	Instruction Prompt	0.87	0.98	0.03	0.41	0.78
	RAG	0.87	0.97	<b>0.13</b>	0.42	0.79
	Dynamic Fusion	<b>0.97</b>	<b>0.99</b>	0.06	<b>0.50</b>	<b>0.84</b>
Qwen	Instruction Prompt	0.98	0.99	0.03	0.45	0.84
	RAG	0.79	0.86	<b>0.14</b>	0.47	0.72
	Dynamic Fusion	<b>0.98</b>	<b>0.99</b>	0.08	<b>0.51</b>	<b>0.85</b>

**P** = Professionalism; **A** = Actionability; **E** = Empathy; **R** = Relevance; **O** = Overall Quality (weighted).

# Results

## How Well Do the Methods Perform?

We evaluate responses generated by:

- **Instruction Prompt**
- **Retrieval-Augmented Generation (RAG)**
- **Dynamic Fusion (Proposed)**

Across three LLMs:

- LLaMA 3.1 8B Instruct
- Mistral 8B Instruct
- Qwen2.5 7B Instruct

Model	Method	P	A	E	R	O (Overall)
LLaMA	Instruction Prompt	0.74	0.52	0.06	0.43	0.55
	RAG	0.96	0.63	0.22	0.40	0.70
	Dynamic Fusion	0.92	0.97	0.04	0.46	0.81
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We evaluate responses generated by:

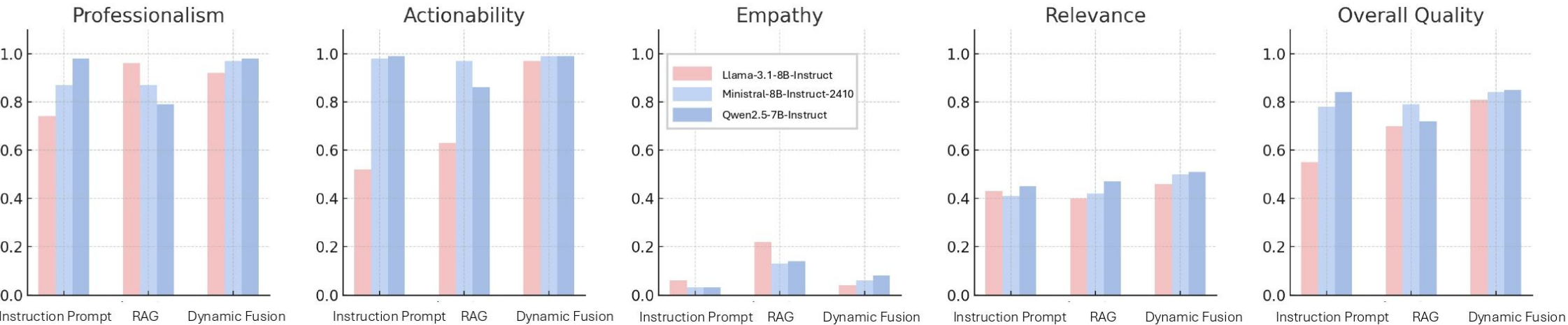
- **Instruction Prompt**
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# Conclusions

## Key Findings

- **Large Language Models (LLMs)** show strong potential for assisting in real-time crisis communication on social media.
- **Instruction Prompt** and **RAG** methods each have strengths:
  - Instruction Prompts offer structure response.
  - RAG improves factual grounding and reduces hallucinations.
- Our proposed **Dynamic Fusion** method consistently delivers the **highest overall response quality**, combining:
  - Professional tone
  - Clear, actionable guidance
  - Grounded information
  - Balanced relevance



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*Dynamic Fusion offers a promising path to building **scalable, trustworthy AI responders** that can support affected individuals during crises.*

# Limitations & Future Work

## Current Limitations

- **Single Crisis Scenario**
  - Tested only on **Hurricane Irma** tweets
  - May not generalize across **other disaster types** (e.g., earthquakes, pandemics)
- **Fusion Agent Simplicity**
  - Fusion currently relies on **basic score comparison and selection**
  - Might overlook deeper reasoning or nuanced combinations
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  - Dynamic Fusion improved professionalism & actionability
  - But **still lags in empathetic tone** compared to human responders

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## Future Work

- **Expand to multiple crisis types**
  - Apply to floods, wildfires, and health emergencies
  - Test multilingual and multicultural variations
- **Improve Fusion Strategy**
  - Integrate **Chain-of-Thought (CoT)** reasoning to guide how components are fused
  - Explore **adaptive prompting or ensemble decision-making**
- **Real-Time Deployment Potential**
  - Collaborate with **NGOs or emergency response teams**
  - Enable LLMs to act as **first-line information assistants**

# Thank You!

Contact: [AnirbanSahaAnik@my.unt.edu](mailto:AnirbanSahaAnik@my.unt.edu)

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