

## QUDSELECT

# Selective Decoding for Questions Under Discussion Parsing



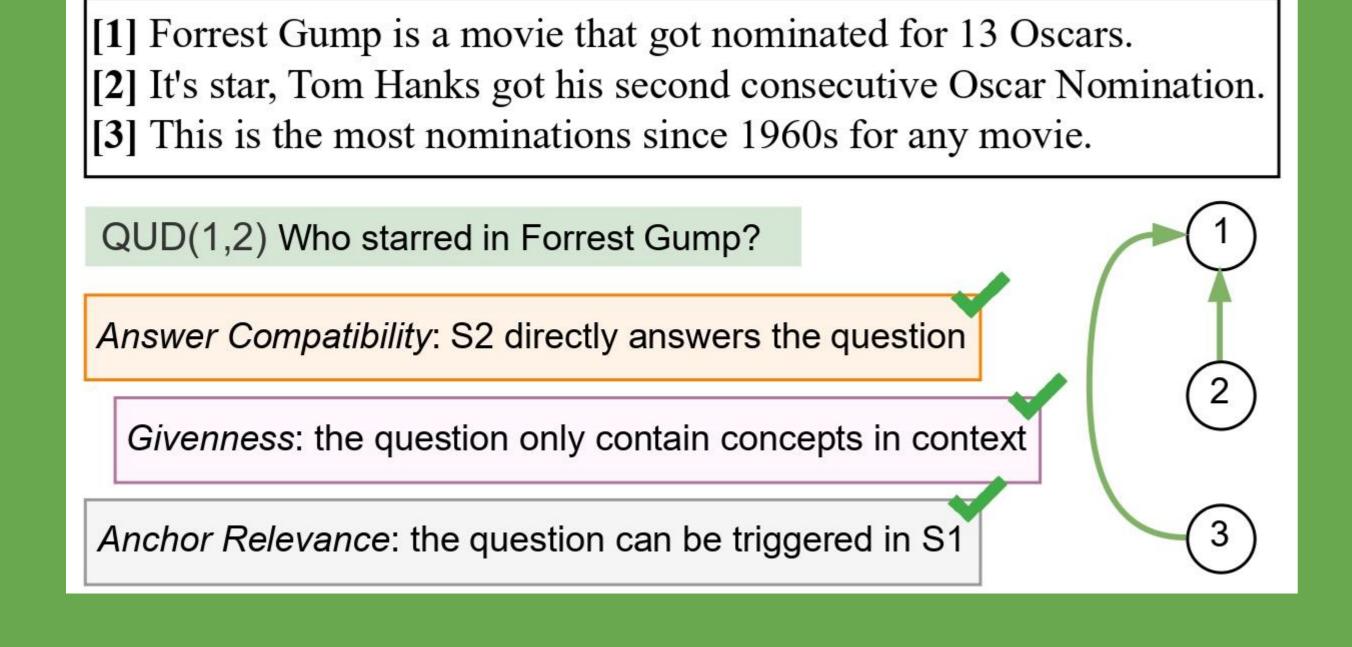


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# Parse complex articles in a human-friendly manner as questions with QUDSELECT!!



Joint Framework to parse QUD structures by integrating key theoretical criteria:

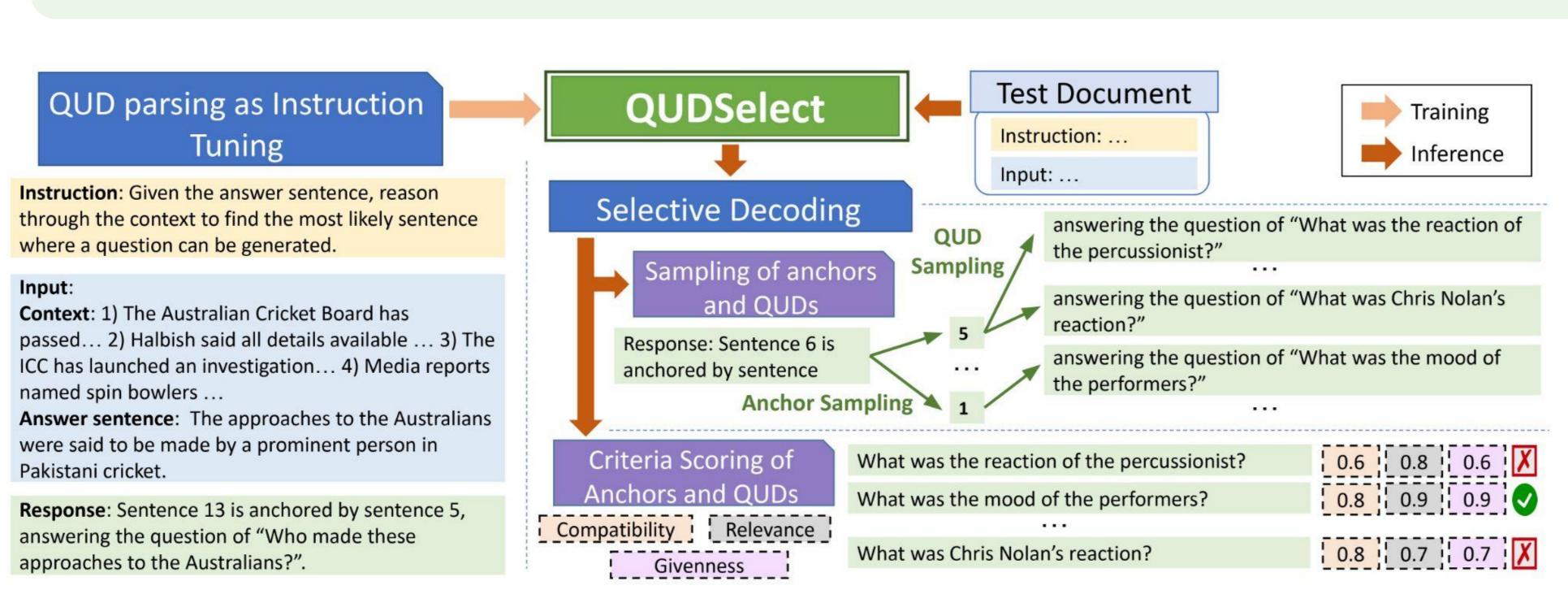
**Answer Compatibility** 

**Givenness** 

**Anchor Relevance** 

We view QUD parsing as instruction tuning task and selectively decode candidate questions and anchors.

### **QUDSELECT Framework**

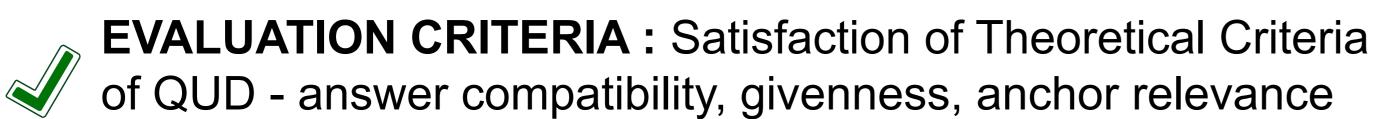


- We first instruction tune a joint QUD parser. Given the answer sentence, models are instructed to predict the anchor and question together.
- Then we propose **selective decoding** where we apply the three key **principles of QUD as our criteria** to assess the quality of generated (anchor sentence, question) pairs and select the best.
- We implement reference-free and training-free scorers for each of them, namely, answer compatibility, givenness and anchor relevance.

### **Experimental Setup**

DATASET: DCQA (22k questions, 606 news articles)

BASELINES: LLaMA2-7B, Mistral-7B, Pipeline, GPT-4

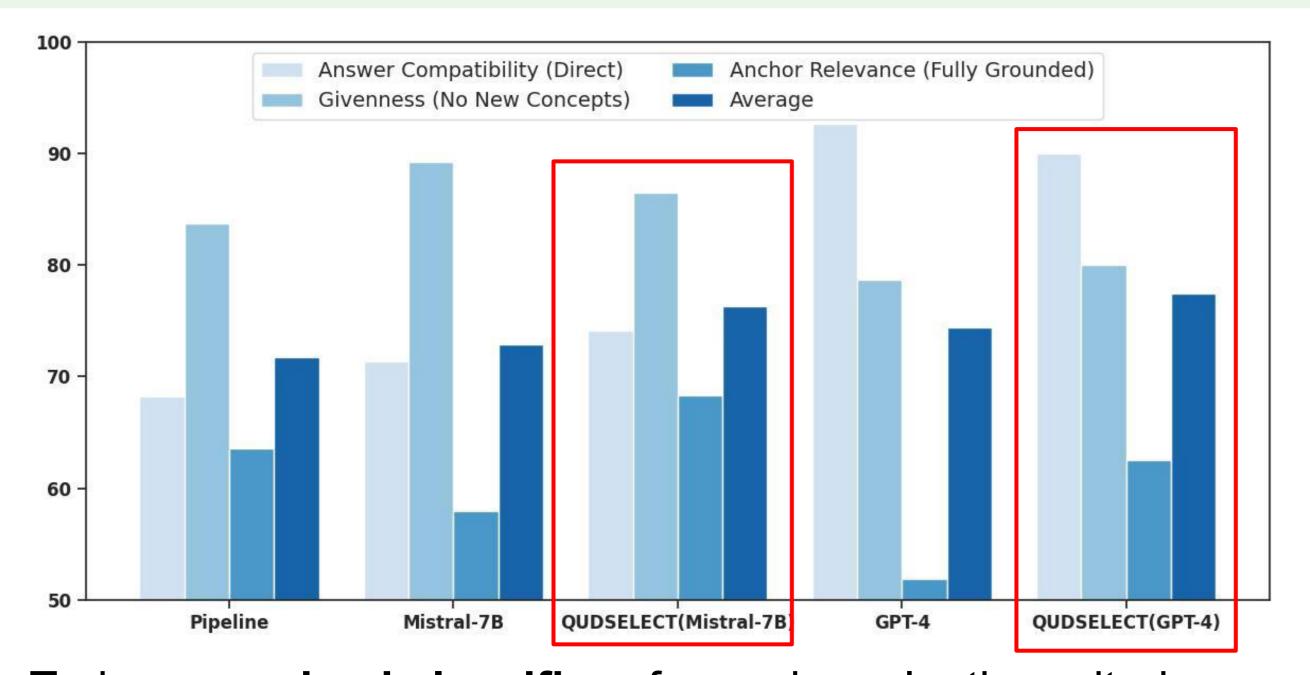


#### **Human Evaluation**

Model	l .	wer Comp Unfocus.	•	No New (†)	Givenness Ans. leak. (↓)	<b>Hall.</b> (↓)	The second secon	chor Relevan Partial. G.		<b>Avg.</b> (†)
HUMAN EVALUATION										
Pipeline	52.5	15.0	32.5	53.8	28.7	17.5	50.0	32.5	17.5	52.1
Mistral-7B	67.0	15.4	17.6	60.3	23.6	16.1	58.6	29.0	12.4	62.0
+ QUDSELECT	67.1	20.0	12.9	77.6	20.0	2.4	68.2	24.7	<b>7.</b> 1	71.0

QUDSELECT outperforms baselines by ~9% on human evaluation. Human annotators find that QUDSELECT leads to **directly answerable questions**, **fully grounds** in context and **satisfies givenness**.

#### **Automatic Evaluation**

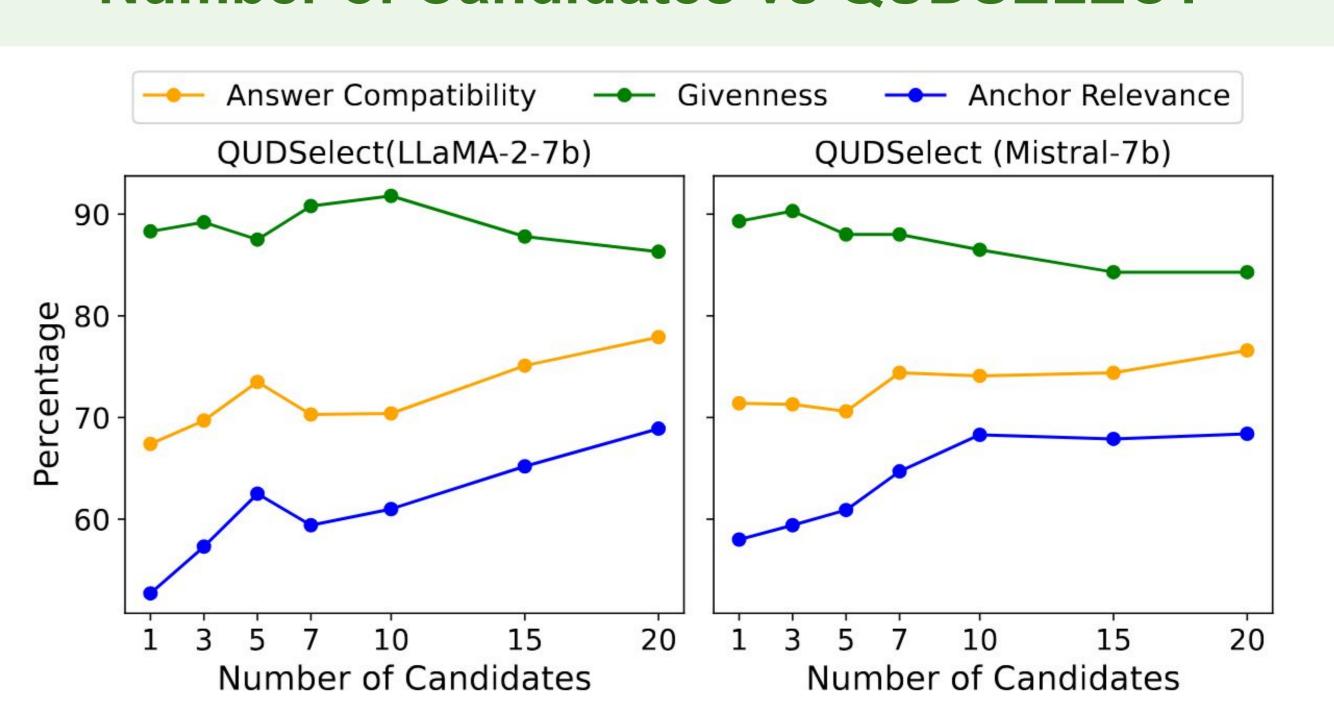


- Train supervised classifiers for each evaluation criterion on expert annotated data from QUDEVAL.
- Our automatic evaluators achieve average macro F1 of 0.47 across all evaluation criteria.

## **QUDs generated by Different Models**

#### Pipeline (Ko et al. (2023)) XNon answer XAnswer leakage ✓ Partially grounded Answer: $s_3$ Anchor: $s_2$ QUD: "What does Glenn think is the future outlook on nuclear materials?" XNonsensical question Answer: $s_4$ Anchor: $s_2$ QUD: "Who is the Sen. Glenn from?" LLaMA2 Answer: $s_4$ Anchor: $s_3$ QUD: "What is deadly contra- XNon answer \( \strace{N} \) No new concepts \( \strace{X} \) Partially grounded band?" Answer: $s_3$ Anchor: $s_1$ QUD: "Why is it difficult to trace $\nearrow$ No new concepts $\checkmark$ Fully grounded nuclear material?"" **QUDSELECT (LLaMA2)** Answer: $s_4$ Anchor: $s_2$ QUD: "Who requested the report? Answer: $s_3$ Anchor: $s_1$ QUD: "What is the reason for the $\checkmark$ Indirect Answer $\checkmark$ No new concepts $\checkmark$ Partially grounded inability to trace nuclear material?" **QUDSELECT** (Mistral) ✓ Direct answer ✓ No new concepts ✓ Fully grounded Answer: $s_3$ Anchor: $s_1$ QUD: "Why is it important that U.S. exports of nuclear material cannot be adequately traced from country to country?" ✓ Direct answer ✓ No new concepts ✓ Fully grounded Answer: $s_4$ Anchor: $s_2$ QUD: "Who commissioned the report?"

### **Number of Candidates vs QUDSELECT**



We see an **upward trend as k grows** for **Answer Compatibility** and **Anchor Relevance** while Givenness is sacrificed by a small margin for better overall performance.