Discursive Socratic Questioning:
Evaluating the Faithfulness of Language Models' Understanding of Discourse Relations

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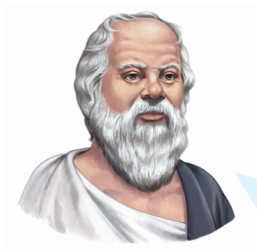
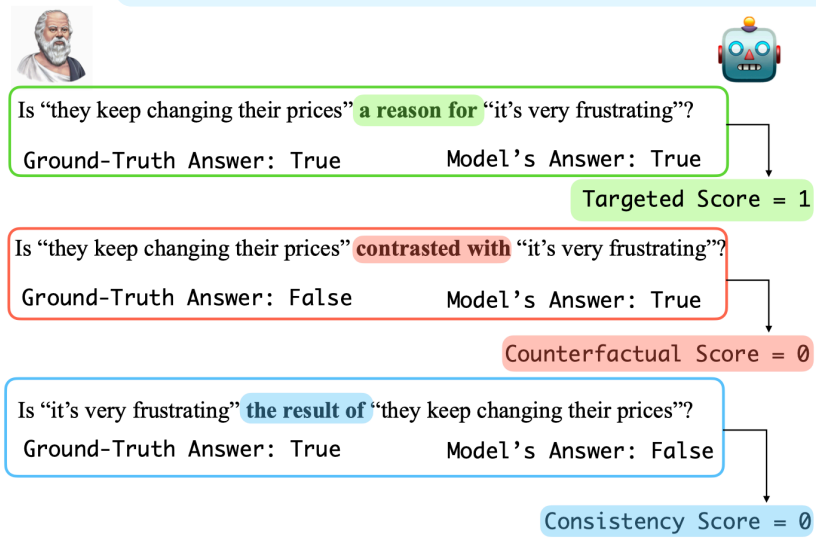


Socrates 🇬🇷
470 – 399 BC

Want to know how well LLMs understand discourse relations? We propose an end-to-end automatic scoring framework for discourse relations, leveraging LLMs in a Socratic style.



Discourse relation: Contingency. Cause.Result

Arg1: When I want to buy, they run from you - they keep changing their prices.

Arg2: It's very frustrating.

Salient signal.

Input X
{
"Discourse relation": ...
"Arg1": ...
"Arg2": ...
"Event1": ...
"Event2": ...
"Event relation (ER)": ...
}

Output y
{
"DR summary": ...
"Event1 Comprehension": ...
"Event2 Comprehension": ...
"What if ER holds": ...
"What if ER does not hold": ...
"Predicting ER": ...
"Final prediction": ...
}

	A1&A2	A1&IC	A2&ICL
Agreements	85.2%	85.2%	83.7%
Cohen's κ	38.5%	48.8%	44.9%
Success Rate	/	95.8%	93.8%

What to ask: In-context learning to annotate salient signals.

Algorithm 1 DiSQ interrogates a language model.

Input: Discourse d and its corresponding questions $\mathcal{Q}$.
$\mathcal{H} = \{\varnothing\}$ ▷ The history is initialized.
Stage 1: Targeted and Counterfactual QA
for q_i in $\mathcal{Q}_t$ and $\mathcal{Q}_c$ **do**
  $a_i = \text{LM}(q = q_i, c = d)$ ▷ The model performs QA. The context c is the discourse d.
  $\mathcal{H} \leftarrow (q_i, a_i)$ ▷ The history is updated.
end for
Stage 2: Converse QA
for (q_i, a_i) in $\mathcal{H}$ **do**
  $\tilde{q} = Lookup(q, \{\tilde{\mathcal{Q}}_c, \tilde{\mathcal{Q}}_t\})$ ▷ Look up the converse question in converse question sets.
  $\tilde{a_i} = \text{LM}(q = \tilde{q_i}, c = d, (q_i, a_i) \in \mathcal{H})$ ▷ The model executes QA on the converse question, $\tilde{q_i}$, optionally utilizing the previous response (q_i, a_i) as supplemental context.
  $\mathcal{H} \leftarrow (\tilde{q_i}, \tilde{a_i})$ ▷ The history is updated.
end for
Output: $\mathcal{H}$

Targeted question:
Is A the result of B?

Counterfactual question:
Is A contrasted with B?
Is A the example with B?
Is A an alternative of B?
...

Converse question:
(Given you answered A is the result of B.) Is B the reason of A?

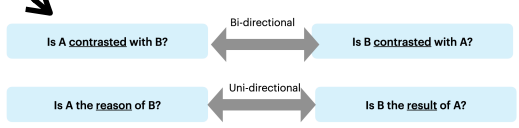
Type	Formalization	Expected Answer	Score
Targeted	$\mathcal{Q}_t = \{QG(s_1, s_2, r)\}$	True	s_t
CF	$\mathcal{Q}_c = \{QG(s_1, s_2, r')\}$	False	s_{cf}
Converse	$\tilde{\mathcal{Q}}_t = \{QG(s_2, s_1, \overleftarrow{r})\}$	Equivalent to original	s_{con}

$$s_t = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}[a_i = True], q_i \in \{\mathcal{Q}_t, \tilde{\mathcal{Q}}_t\}$$

$$s_{cf} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}[a_i = False], q_i \in \{\mathcal{Q}_c, \tilde{\mathcal{Q}}_c\}$$

$$s_{con} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{1}[a_i = \tilde{a}_i], q_i \in \mathcal{Q}, \tilde{q}_i \in \tilde{\mathcal{Q}}$$

$$s_{disq} = s_t \times s_{cf} \times s_{con}$$



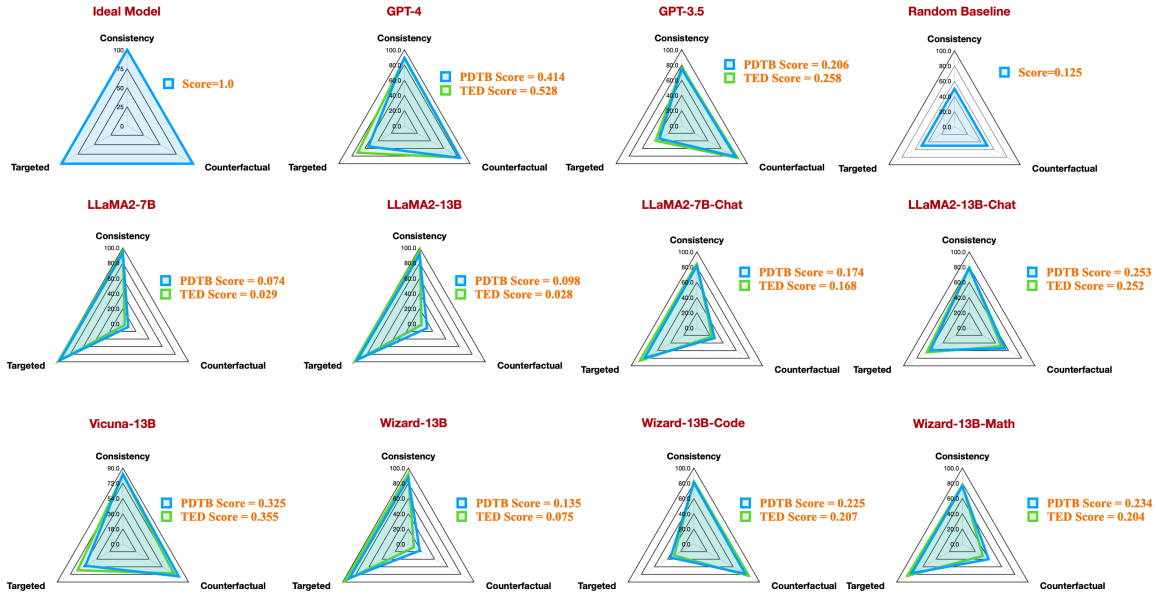
How to ask: DiSQ is composed of **(1)** targeted questions, **(2)** counterfactual questions and **(3)** converse questions. DiSQ Scores is a multiplication of the three aspects.

Discourse relation (R)	Event relation (r)	Q Type	# of Q
Comparison.Concession	deny or contradict with	Bi-	1,764
Comparison.Contrast	contrast with	Bi-	876
Contingency.Reason	reason of	Uni-	3,264
Contingency.Result	result of	Uni-	2,796
Expansion.Conjunction	contribute to the same situation	Bi-	4,596
Expansion.Equivalence	equivalent to	Bi-	420
Expansion.Instantiation	example of	Uni-	2,352
Expansion.Level-of-detail	provide more detail about	Uni-	3,888
Expansion.Substitution	alternative to	Uni-	216
Temporal.Asynchronous	happen before/after	Uni-	1,368
Temporal.Synchronous	happen at the same time as	Bi-	840
Total			22,380

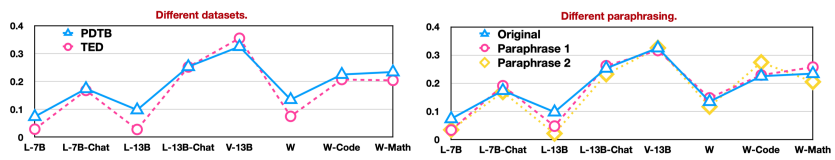
Question statistics for PDTB dataset.

Evaluation setup: PDTB and TED-MDB dataset. Zero-shot QA.

Evaluated models: **(1) Closed-source models:** GPT-4 / GPT-3.5. **(2) Open-source models:** LLaMA family; Vicuna model; Wizard family.



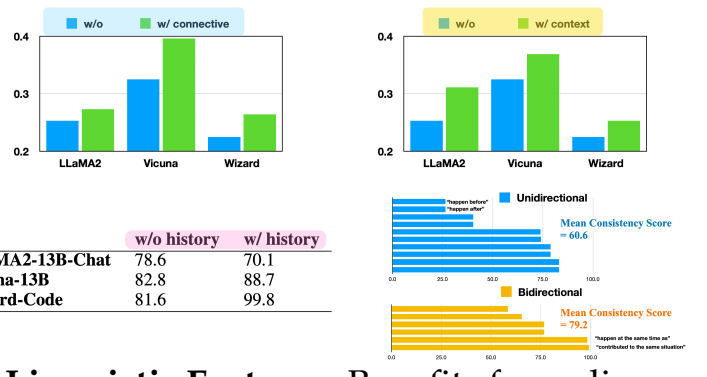
Overall performance (RQ1): **(1)** Gap between Close- and Open source models; **(2)** Benefits from further fine-tuning; **(3)** Consistency between the two datasets.



RQ2: DiSQ Scores are consistent.

	Models	Overall	Comp.Conce	Comp.Contra	Cont.Reason	Cont.Result	Exp.Conj	Exp.Equiv	Exp.Inst	Exp.Detail	Exp.Subst	TempAsync	TempSync
	1. Random Basline	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
PDTB	2A. LLaMA2-7B	0.074	0.029	0.083	0.094	0.095	0.076	0.056	0.087	0.067	0.156	0.035	0.048
PDTB	3A. LLaMA2-7B-Chat	0.174	**0.231**	0.431	0.131	0.174	0.213	**0.104**	0.120	0.150	0.199	0.108	0.040
PDTB	4A. LLaMA2-13B	0.098	0.037	0.100	0.082	0.097	0.127	0.101	0.113	0.107	0.086	0.084	**0.092**
PDTB	5A. LLaMA2-13B-Chat	**0.253**	**0.193**	**0.477**	0.129	0.172	**0.288**	**0.157**	**0.326**	**0.373**	**0.291**	0.195	0.028
PDTB	6A. Vicuna-13B	**0.325**	0.087	**0.513**	**0.200**	**0.353**	**0.369**	0.000	**0.334**	**0.462**	0.195	**0.511**	0.069
PDTB	7A. Wizard	0.135	**0.221**	0.256	0.067	0.107	0.170	0.072	0.167	0.128	0.108	0.097	0.082
PDTB	8A. Wizard-Code	0.225	0.032	0.268	**0.175**	**0.287**	0.121	0.008	0.283	0.329	0.174	**0.545**	**0.109**
PDTB	9A. Wizard-Math	0.234	0.132	0.264	**0.241**	0.286	0.192	0.046	0.240	0.323	0.201	0.240	**0.135**
PDTB	10A. GPT-3.5	0.206	0.151	0.278	0.082	0.161	0.246	0.067	0.257	0.262	**0.232**	0.388	0.000
PDTB	11A. GPT-4	**0.414**	0.053	**0.567**	0.119	**0.351**	**0.610**	**0.192**	**0.659**	**0.481**	**0.422**	**0.692**	0.000

RQ3: Minority classes are still challenging.



	w/o history	w/ history
LLaMA2-13B-Chat	78.6	70.1
Vicuna-13B	82.8	88.7
Wizard-Code	81.6	99.8

RQ4: Linguistic Features: Benefits from discourse connectives, discourse context, and historical QAs.

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