Count Information: Retrieving and Estimating Cardinality of Entity Sets from the Web

Shrestha Ghosh

Doctoral Thesis Defense

Outline

1. Introduction
2. Contributions
    - RQ1: Identifying and Aligning Count Information in KBs
    - RQ2: Aggregating Count Information from Web Snippets
    - RQ3: Cardinality Comparison
    - RQ4: Cardinality Estimation
3. Summary
4. Limitations & Future Work
5. Conclusion

1. Introduction

Introduction: Background

Count Information captures the **cardinality** of a **set of entities**, directly as a **count** or as **enumerations**.

	Example 1	**Example 2**
Set of Entities	Nobel Prize Winners in Physics	Physicists in the world
Cardinality / Count	224	~1 million
Enumeration	{Max Planck, Marie Curie, … , }	{Jocelyn Burnell, Peter Higgs, …, }

Ground-truth cardinality of Nobel Prize Winners obtained from NobelPrize(2023) and physicists from Day(2015). Enumerations are obtained from Wikidata, last accessed 27.09.2024.

Introduction: Background

Count Information captures the **cardinality** of a **set of entities**, directly as a **count** or as **enumerations**.

	Example 1	**Example 2**
Set of Entities	Nobel Prize Winners in Physics *crisp, popular*	Physicists in the world *fuzzy, large*
Cardinality / Count	224 *exact*	~1 million *estimate*
Enumeration	{Max Planck, Marie Curie, … , } *complete (224 entities)*	{Jocelyn Burnell, Peter Higgs, …, } *incomplete (33,000 entities)*

Ground-truth cardinality of Nobel Prize Winners obtained from NobelPrize(2023) and physicists from Day(2015). Enumerations are obtained from Wikidata, last accessed 27.09.2024.

Introduction: Knowledge on the Web

1. **Explicit Knowledge**

   Entity-centric KB

Suchaneck et al. (2007), Auer et al. (2007), Vrandečić (2012)

Singhal (2012), Qian (2013), Baidu (2020)

Introduction: Knowledge on the Web

1. **Explicit Knowledge**

   Entity-centric KB

   Aspect-based

Numeric

Saha et al. (2017), Ho et al. (2022)

Negative

Darari et al. (2015), Arnaout et al. (2021)

Temporal

Hoffart et al.(2013), Jain et al. (2020)

Commonsense

Liu and Singh (2004), Tandon et al. (2014), Sap et al. (2019), Romero et al. (2019), Nguyen et al. (2021)

Introduction: Knowledge on the Web

1. **Explicit Knowledge**

   Entity-centric KB

   Aspect-based

2. **Parametric Latent Knowledge**

   Transformer-based language models

GPT4-o and DALL-E AI

LLMs

Radford et al. (2018), Devlin et al. (2019), Raffel et al. (2020), Du et al. (2022)

KBs from LLM

Petroni et al. (2019), Singhania et al. (2023)

Commonsense

Elazar et al. (2019)

Retrieval-augmented generation

Lewis et al. (2020), Izacard and Grave (2021)

Introduction: Accessing Count Information

how many Nobel Prizes won by Marie Curie

Marie Curie / Nobel Prize / Wins / **Count**

2

from KB

Introduction: Accessing Count Information

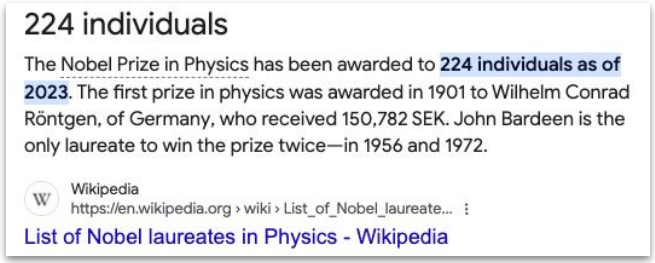
how many Nobel Prizes won by Marie Curie

Marie Curie / Nobel Prize / Wins / **Count**

2

from KB

how many Nobel Prize winners in Physics



from featured snippet

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Marie Curie / Nobel Prize / Wins / **Count**

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from KB

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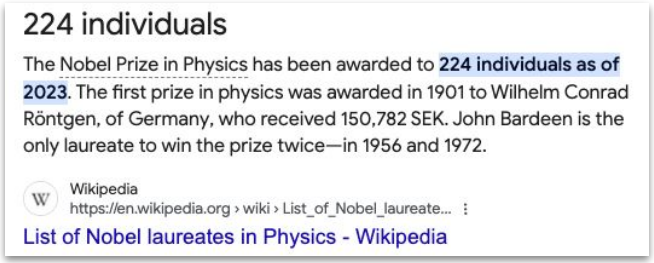
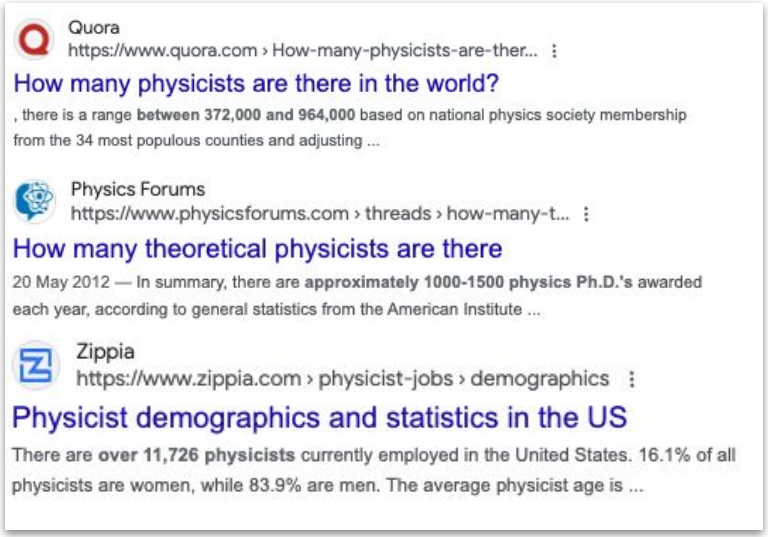


from featured snippet

how many physicists are there in the world



no direct answers

Introduction: Accessing Count Information

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Marie Curie / Nobel Prize / Wins / **Count**

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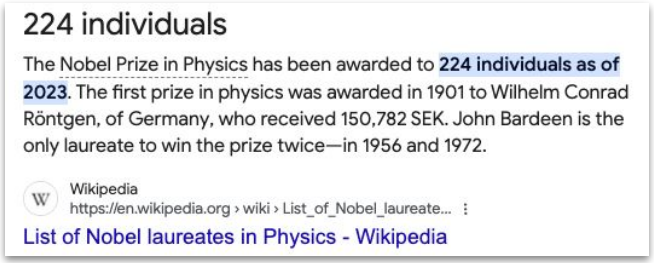

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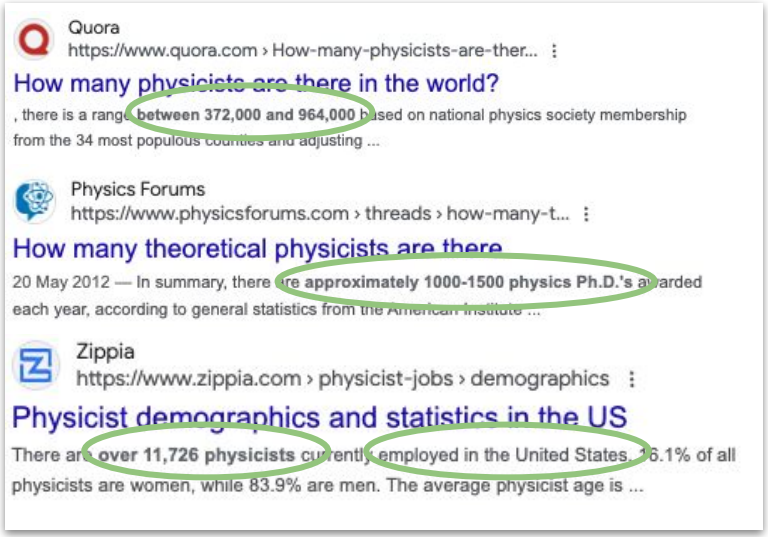

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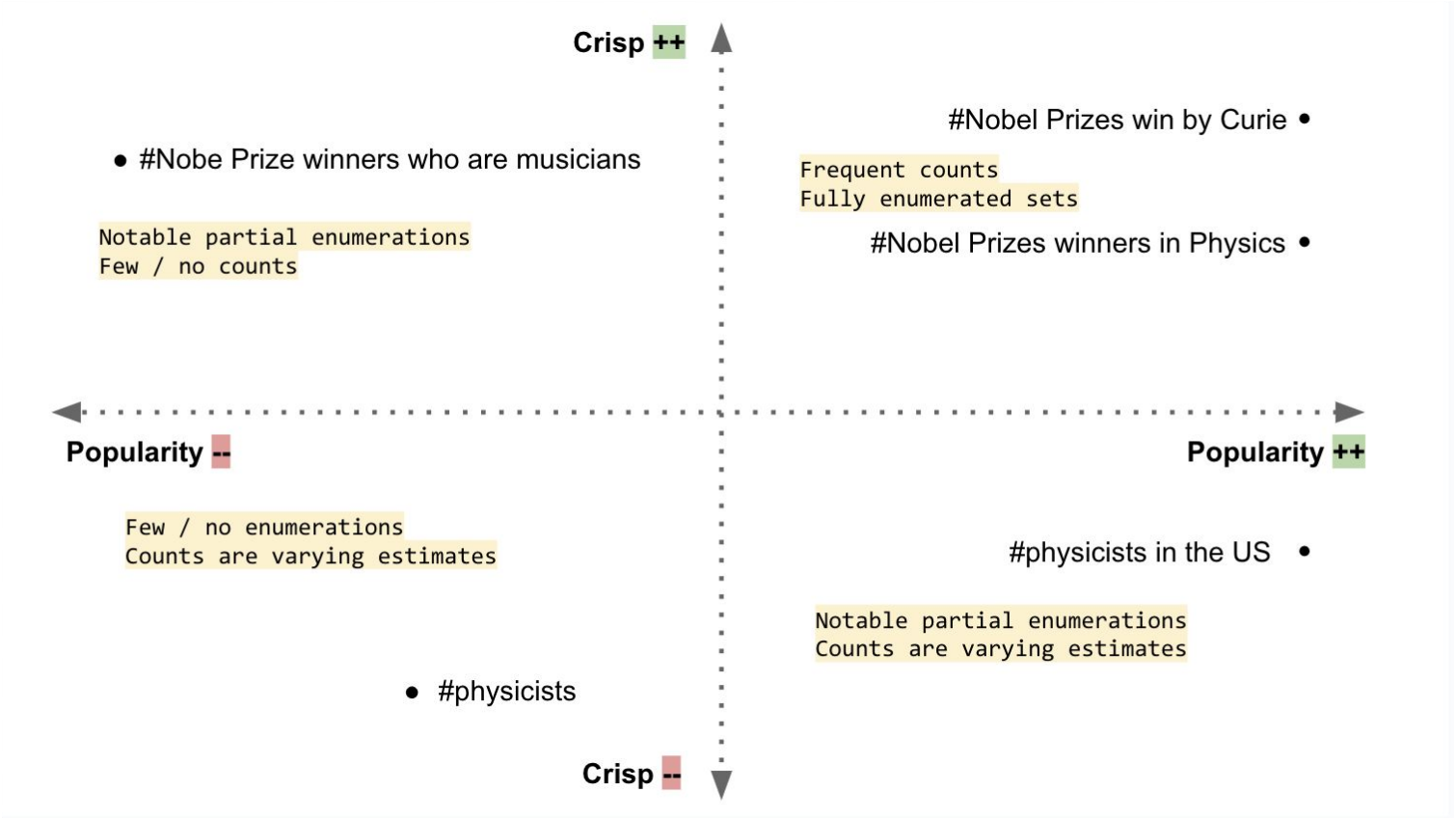
Introduction: Coverage Bias



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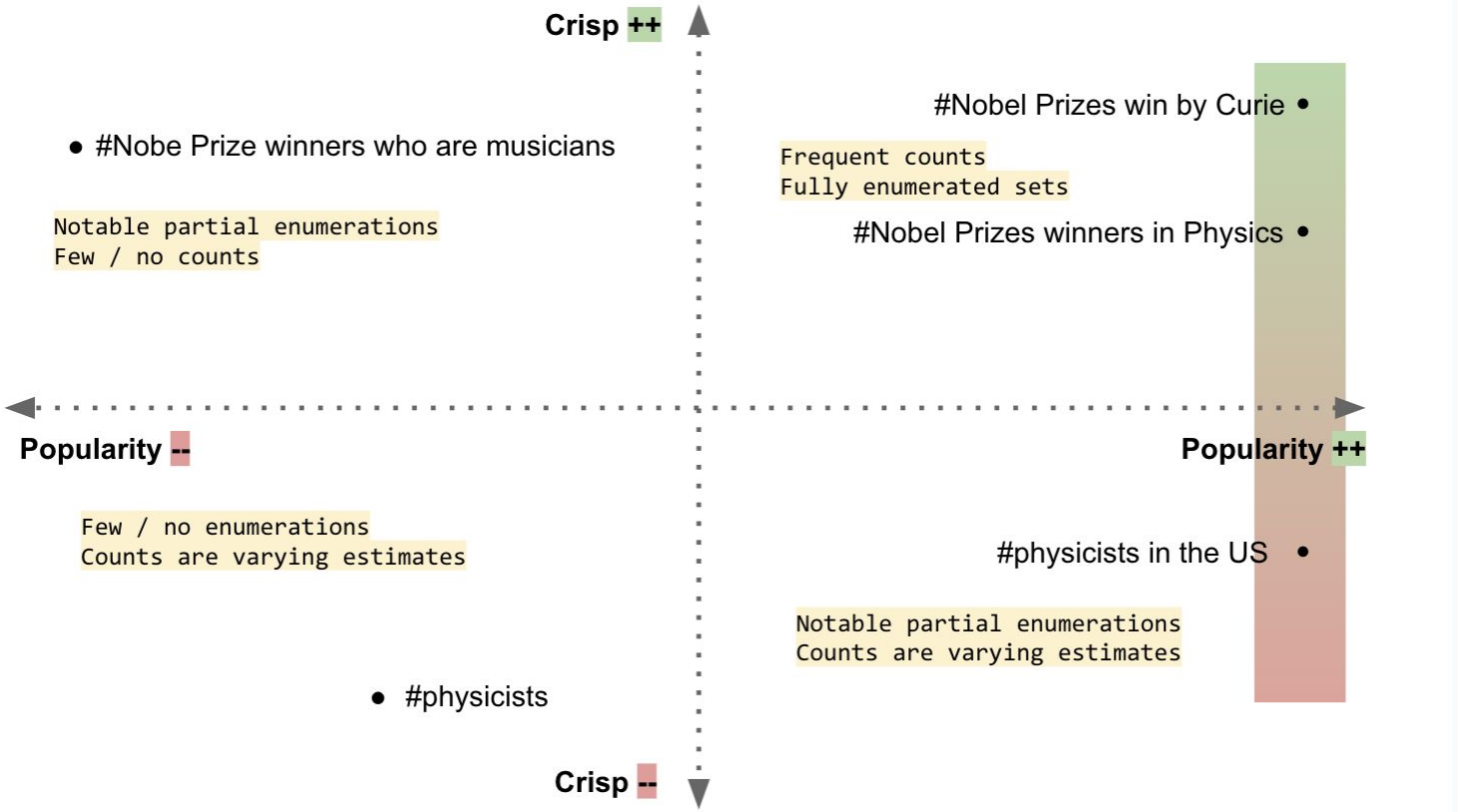

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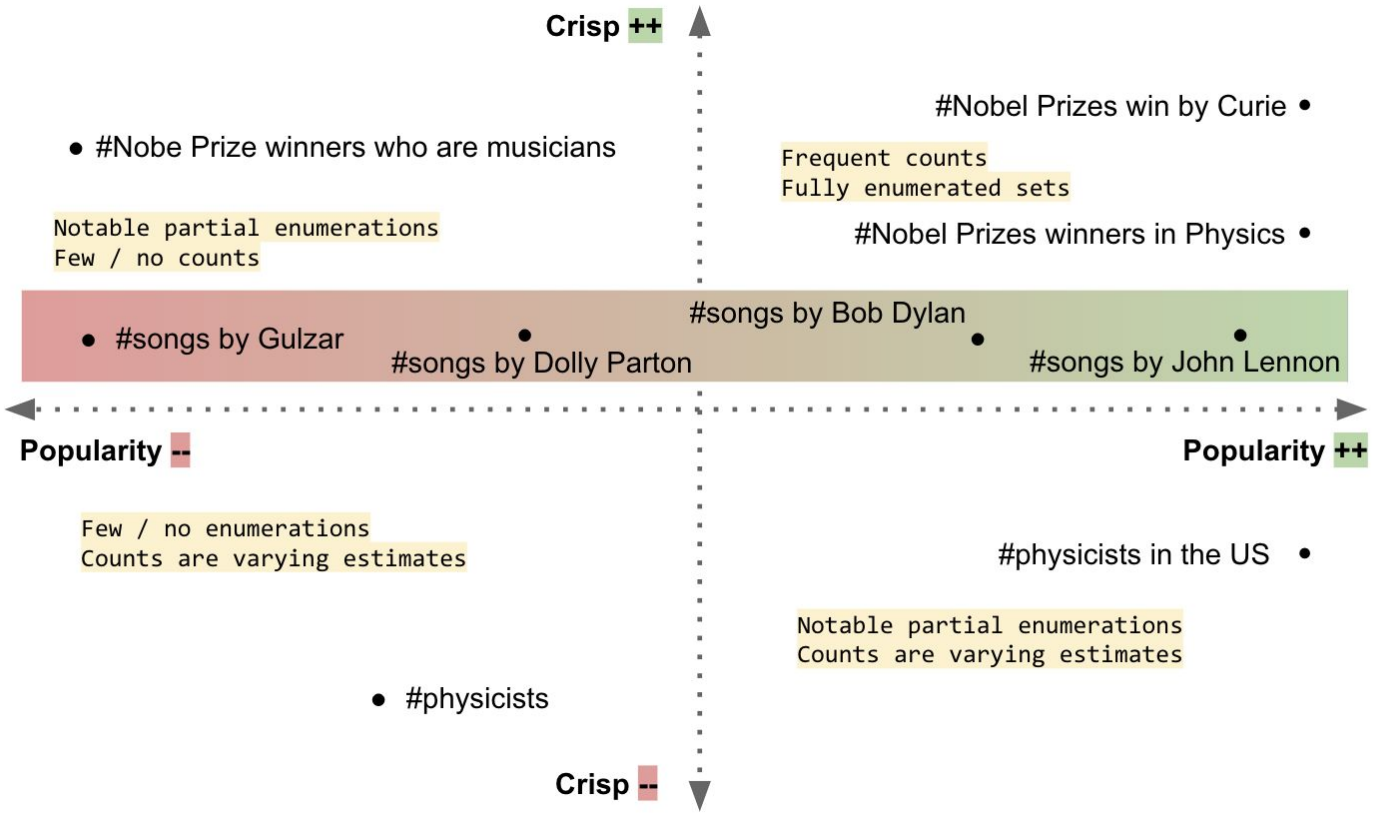

Introduction: Count Question Answering

5%-10% TREC QA datasets contain counts

Mirza et al. (2018)

Count questions not dealt in a principled manner.

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KB QA ad-hoc aggregate over objects

Bast and Hausmann (2015), Diefenbach et al. (2018)

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Benchmarks: exact match, n-gram overlap

SQuAD [Rajpurkar et al. 2016, 2018], LC-QuAD 2.0 [Dubey et al. (2019)]

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Does not transfer to counts

Introduction: Cardinality Estimation

Cardinality estimation from KBs

Trushkowsky et al. (2013), Galárraga et al. (2017), Soulet et al. (2018), Luggen et al. (2019)

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Prone to underestimations

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Depends on single source

2. Contributions

Contributions: Overview

RQ1

Counts in KBs (CounQER)

*How to **identify** and **align predicates** that store count information?*

JWS 2020,
ESWC 2020 (demo)

Contributions: Overview

RQ1. How can we identify and align count information in KBs?

Aggregating objects of (enumerating) predicates often mislead.

number of children of Charlie Chaplin (GT = 11)

child	Charles Chaplin	Victoria Chaplin
	Geraldine Chaplin	Eugene Chaplin
	Michael Chaplin	Jane Chaplin
	Josephine Chaplin	Christopher Chaplin
(Wikidata)	Sydney Chaplin	

number of employees at Saarland University (GT = 1500)

```
select  count(?s) where {
  ?s
    dbp:workInstitution | dbp:workplaces
  dbr:Saarland_University.
}
```

=18

(DBpedia)

Contributions: Overview

RQ1. How can we identify and align count information in KBs?

number of children	11

We can fall back on cardinality storing (counting) predicates.

dbp:academicStaff	1571

number of children of Charlie Chaplin (GT = 11)

child		
	Charles Chaplin	Victoria Chaplin
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JWS 2020, ESWC 2020 (demo)

RQ2

Counts in Web Snippets (CoQEx)

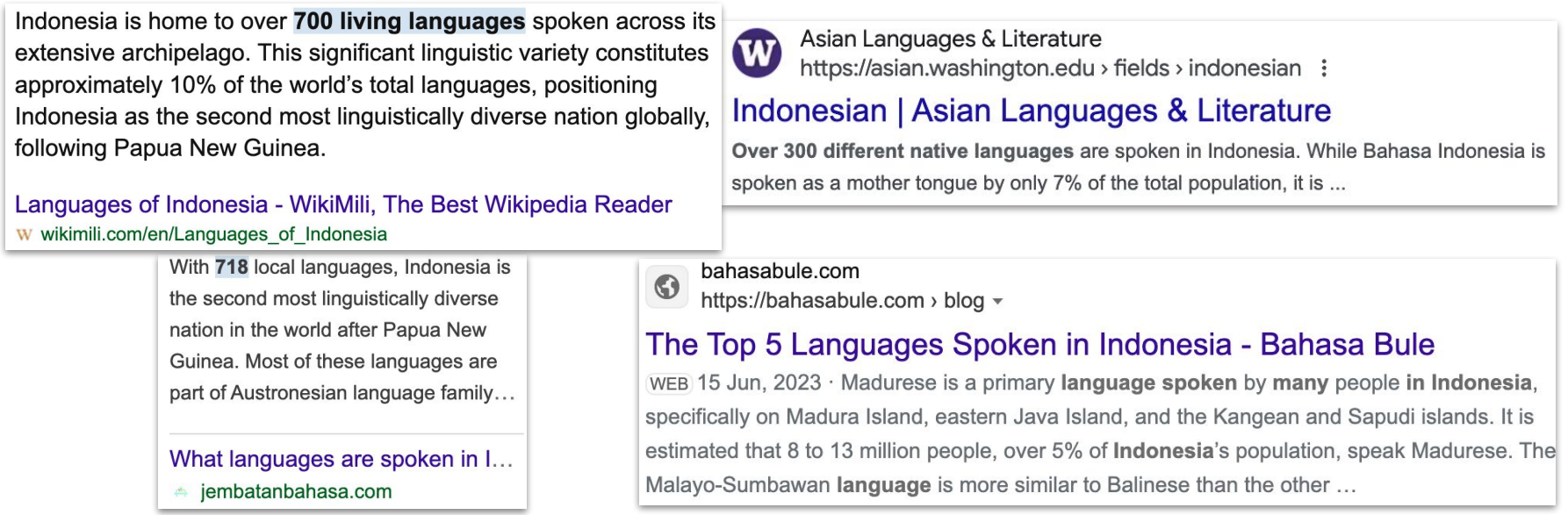
*How to **aggregate counts** and **enumerations** from Web snippets?*

SIGIR 2022, JoWS 2022 WSDM 2023 (demo)

Contributions: Overview

RQ2. How can we aggregate count information from Web snippets?

How many languages are spoken in Indonesia?



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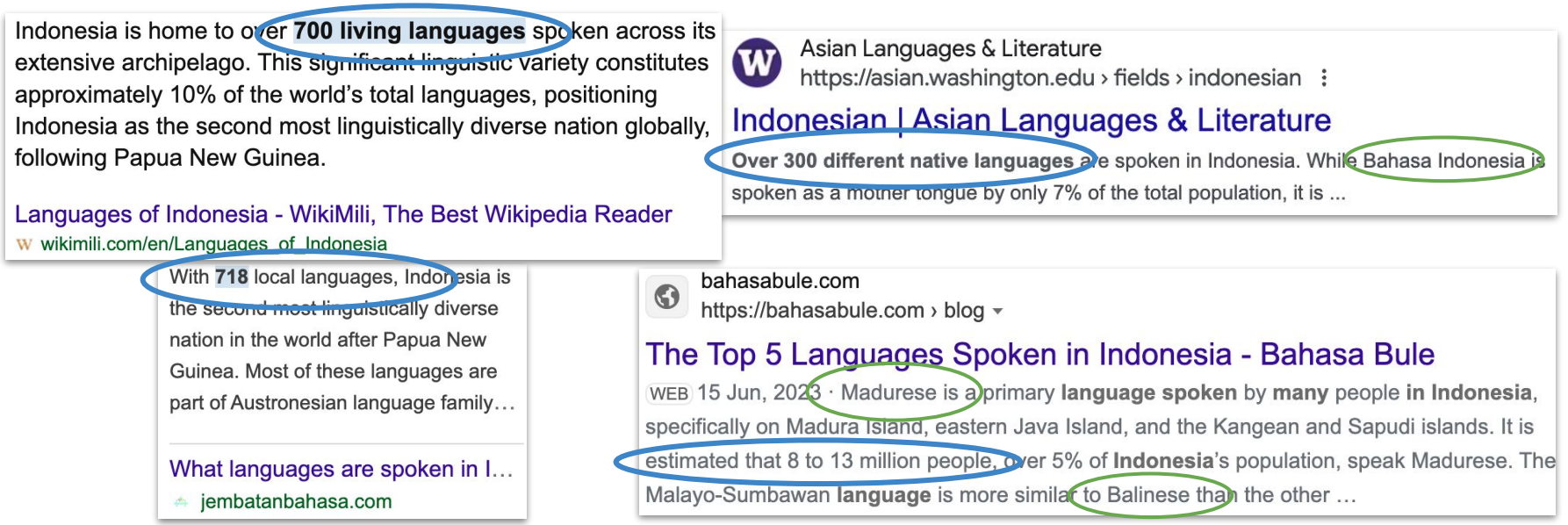

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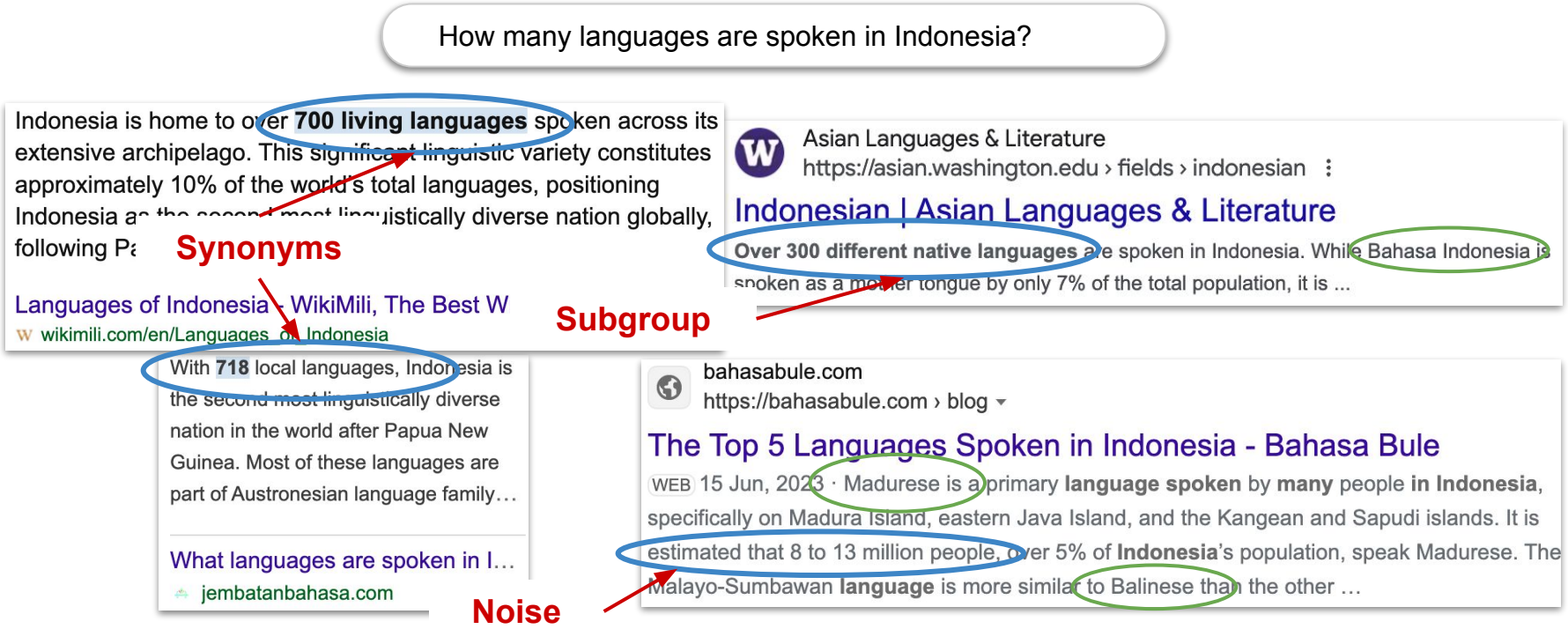

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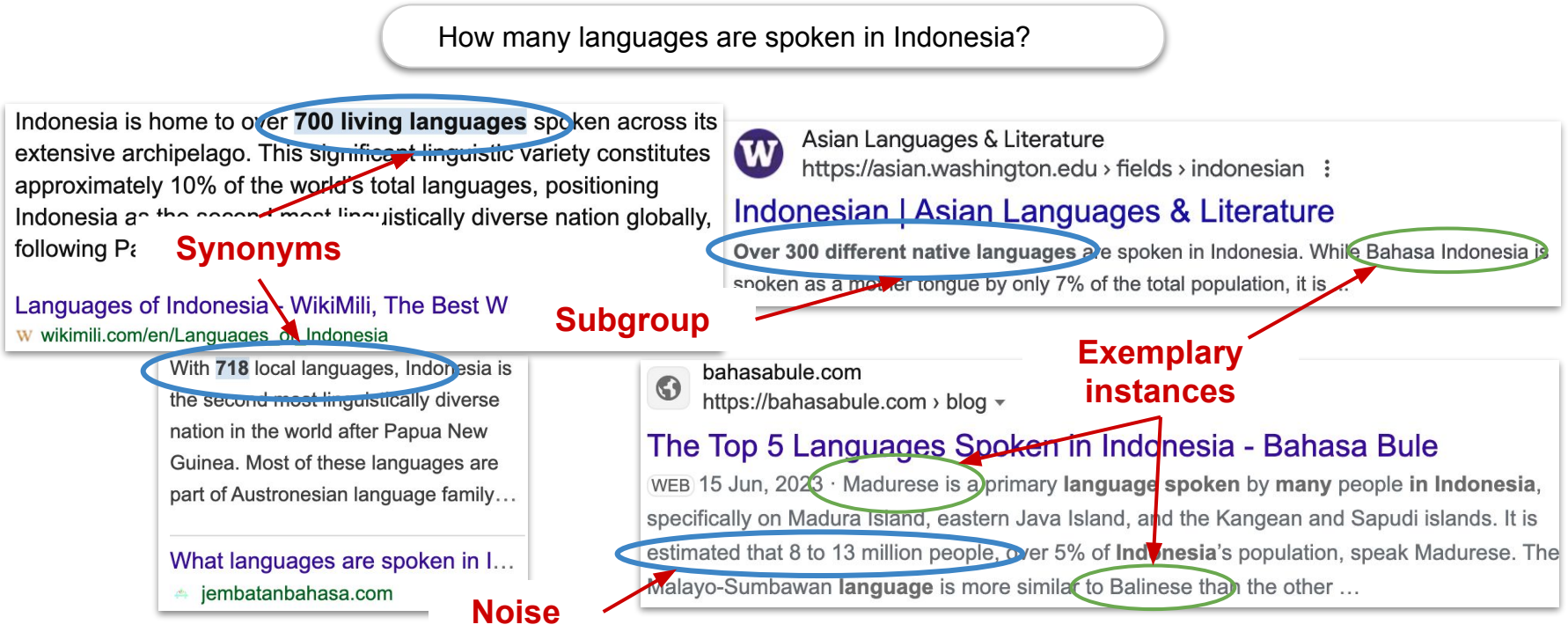

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RQ3

Cardinality Comparison

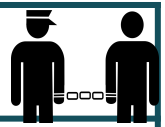
*How to **predict the larger** of two classes of entities?*

WWW 2023

Contributions: Overview

RQ3. How to compare two sets of entities when cardinalities are unreliable?

Are there more **lawyers** than **police officers**?

Sources			
Wikidata	96K	>	8K
SE results	1.3M	>	18K
GPT-3	1.3M	=	1.3M
Ground-truth	3.5M	<	13M

Our approach <

Images credits: https://openclipart.org/
Lawyers and police officers GT: Manually aggregated over countries

Contributions: Overview

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WWW 2023

RQ4

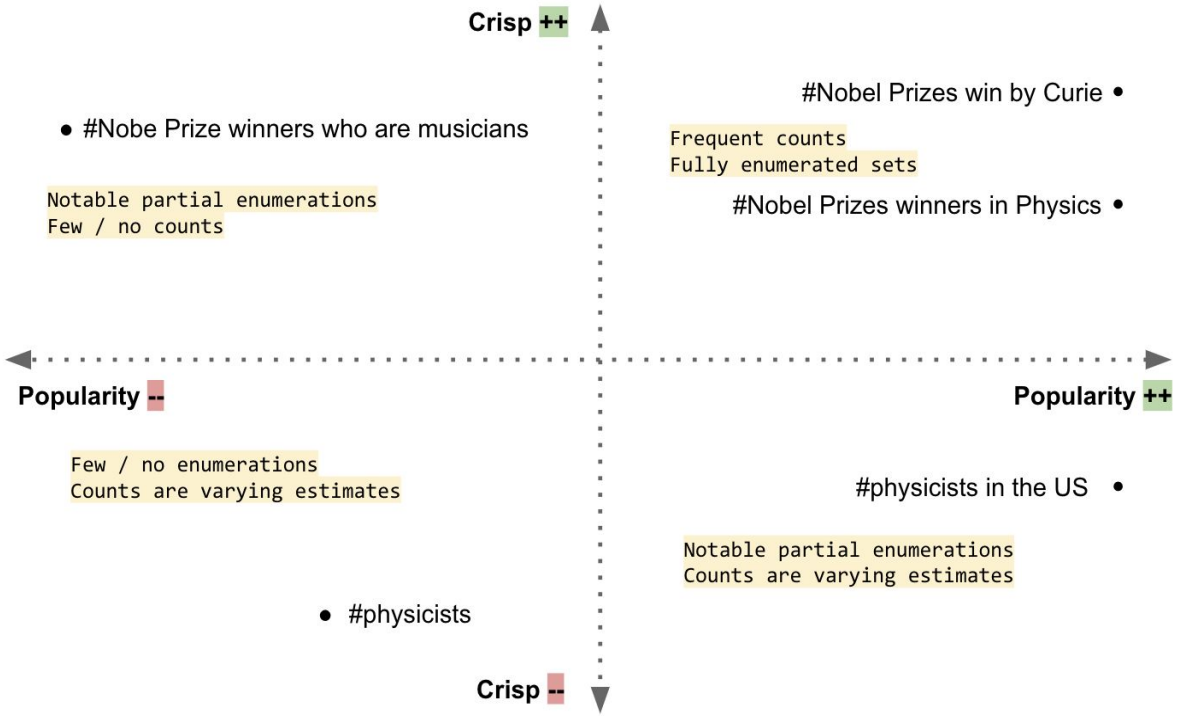
Cardinality Estimation (CardiO)

*How to make **traceable cardinality estimations** in the age of LLMs?*

WWW 2024

Contributions: Overview

RQ4: How to make traceable cardinality estimations in the age of LLMs?



how many physicists are there?

It is difficult to give an exact number of physicists ... However, as of 2021, there are estimated to be over 130,000 physicists globally according to data from the American Physical Society.

Contributions: Overview

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WWW 2023

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WWW 2024

2. Contributions

RQ2: Aggregating Count Information from Web Snippets

Contributions: RQ2

How many languages are spoken in Indonesia?

Indonesia is home to over **700 living languages** spoken across its extensive archipelago. This significant linguistic variety constitutes approximately 10% of the world's total languages, positioning Indonesia as the second most linguistically diverse nation globally, following Papua New Guinea.

Languages of Indonesia - WikiMili, The Best Wikipedia Reader
wikimili.com/en/Languages_of_Indonesia

Asian Languages & Literature
https://asian.washington.edu › fields › indonesian

Indonesian | Asian Languages & Literature

Over 300 different native languages are spoken in Indonesia. While Bahasa Indonesia is spoken as a mother tongue by only 7% of the total population, it is ...

With **718** local languages, Indonesia is the second most linguistically diverse nation in the world after Papua New Guinea. Most of these languages are part of Austronesian language family…

What languages are spoken in I…
jembatanbahasa.com

bahasabule.com
https://bahasabule.com › blog

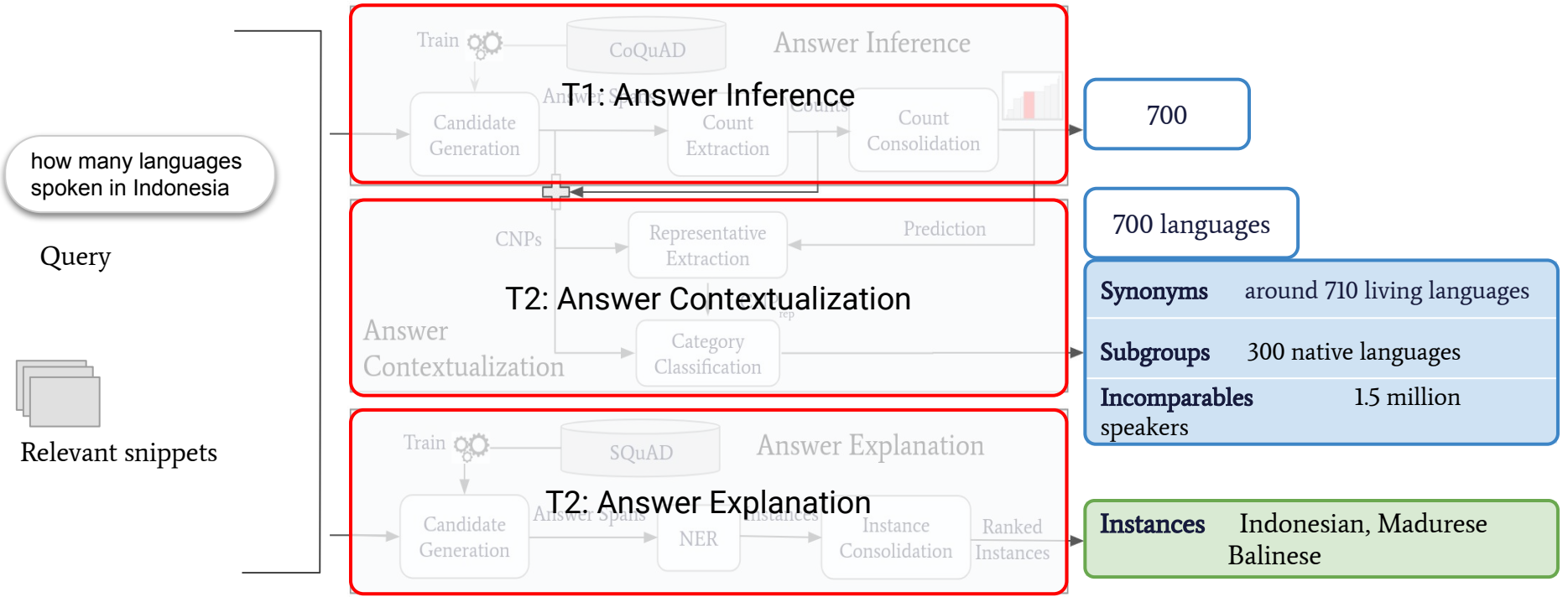
The Top 5 Languages Spoken in Indonesia - Bahasa Bule

WEB 15 Jun, 2023 · Madurese is a primary **language spoken** by **many** people **in Indonesia**, specifically on Madura Island, eastern Java Island, and the Kangean and Sapudi islands. It is estimated that 8 to 13 million people, over 5% of **Indonesia**'s population, speak Madurese. The Malayo-Sumbawan **language** is more similar to Balinese than the other …

Contributions: RQ2: CoQEx

SIGIR 2022, JoWS 2022, WSDM 2023 (demo)

Count **Q**uestion answering with **Ex**planatory evidence



Contributions: RQ2: CoQEx

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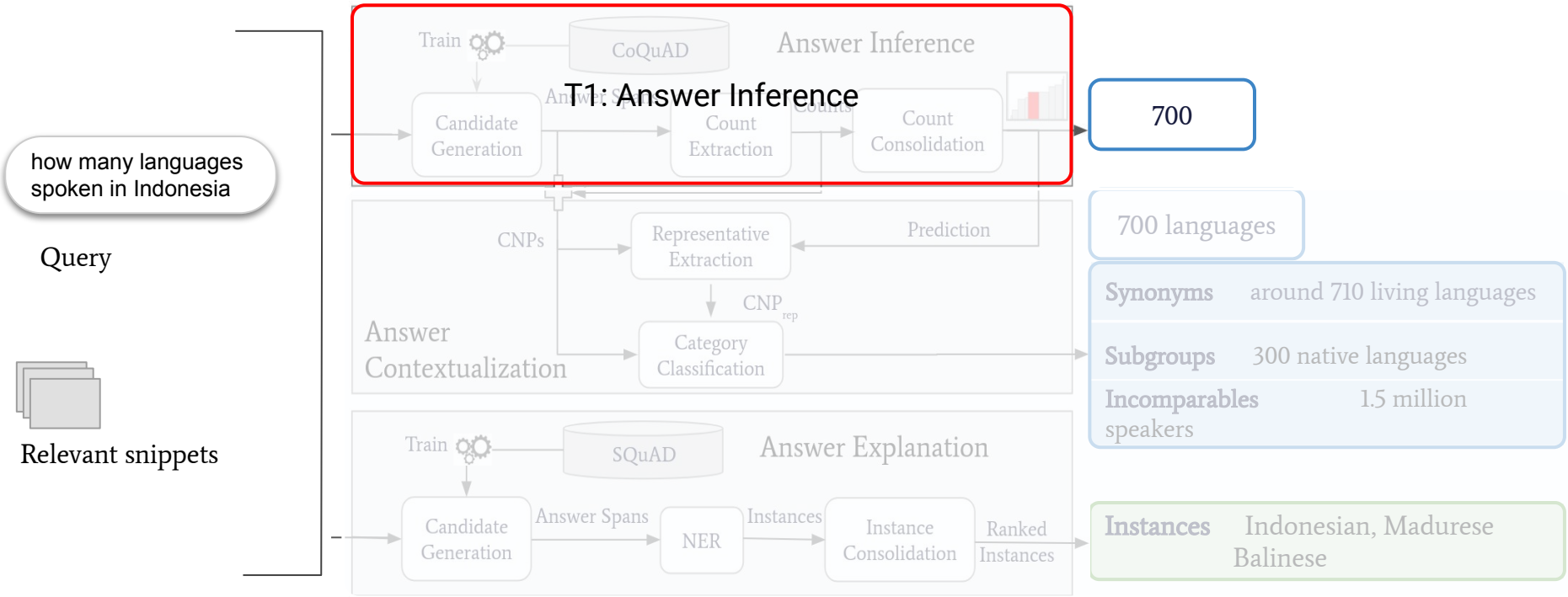
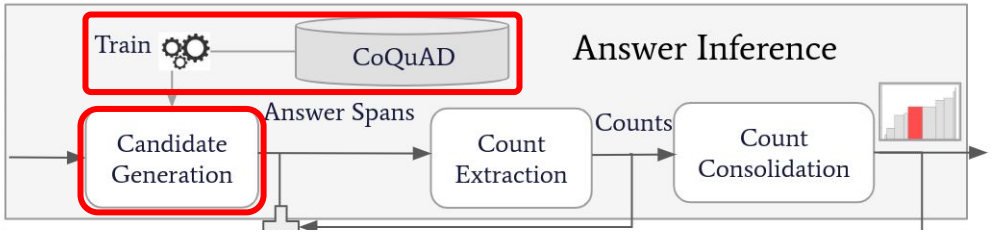


Contributions: RQ2: Answer Inference

how many languages spoken in Indonesia



Snippet

… There are an estimated 710 living languages spoken in Indonesia

Candidate count contexts (strings)

710 living languages 0.96

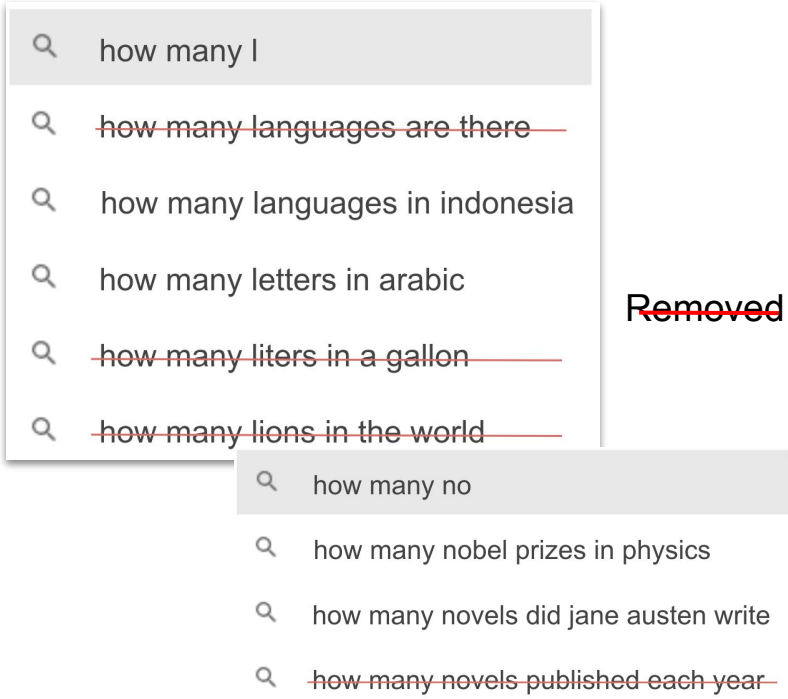
Contributions: RQ2: CoQuAD

Count **Qu**estion **A**nswering **D**ataset

Train a BERT model on candidate extraction.

Automated scraping of count queries.

- Iterative prefixes on Google autocomplete
- Filter out no named-entity, quantity units



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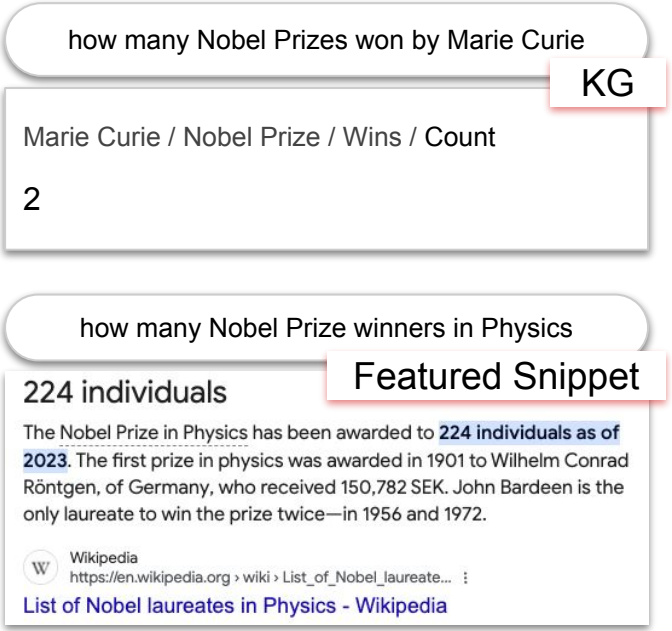
Automated ground-truth extraction for 5K queries

- KG / featured snippet from Google SERP

Quality evaluation

81% silver answer match with gold answers
84% match within ± 10% of gold answers



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Relaxed snippet annotation for 200K web snippets

how many Nobel Prize winners in Physics

224

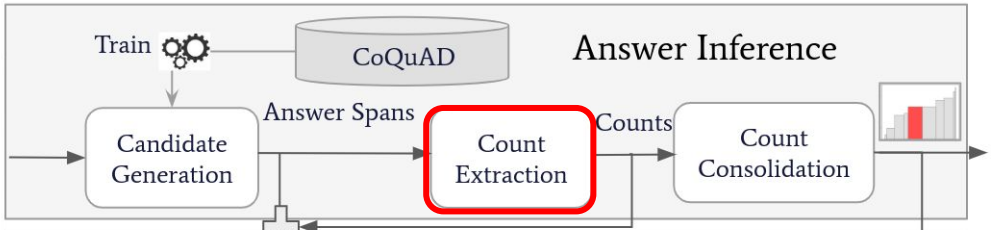
… Physics has been awarded to 224 individuals.

… have been 225 Nobel Prize laureates ..

… Germany has 28 Nobel laureates in Physics..

Contributions: RQ2: Answer Inference

how many languages spoken in Indonesia

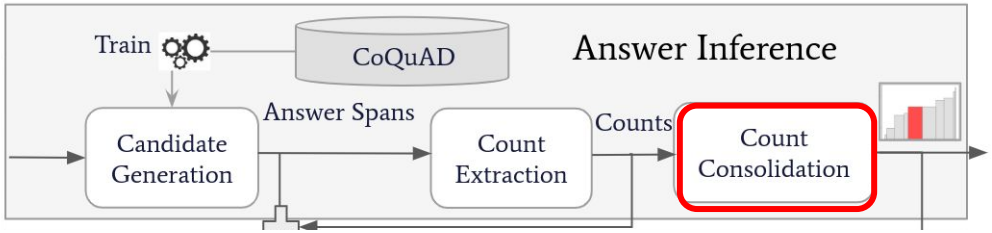


Candidates (strings)		Separate the Counts (integers)
300 native languages	→	300
700 languages	→	700
710 living languages	→	710
1.5 million native speakers	→	1,500,000

Subhro Roy, Tim Vieira, and Dan Roth. 2015. Reasoning about Quantities in Natural Language. TACL (2015).

Contributions: RQ2: Answer Inference

how many languages spoken in Indonesia



700

Count Distribution

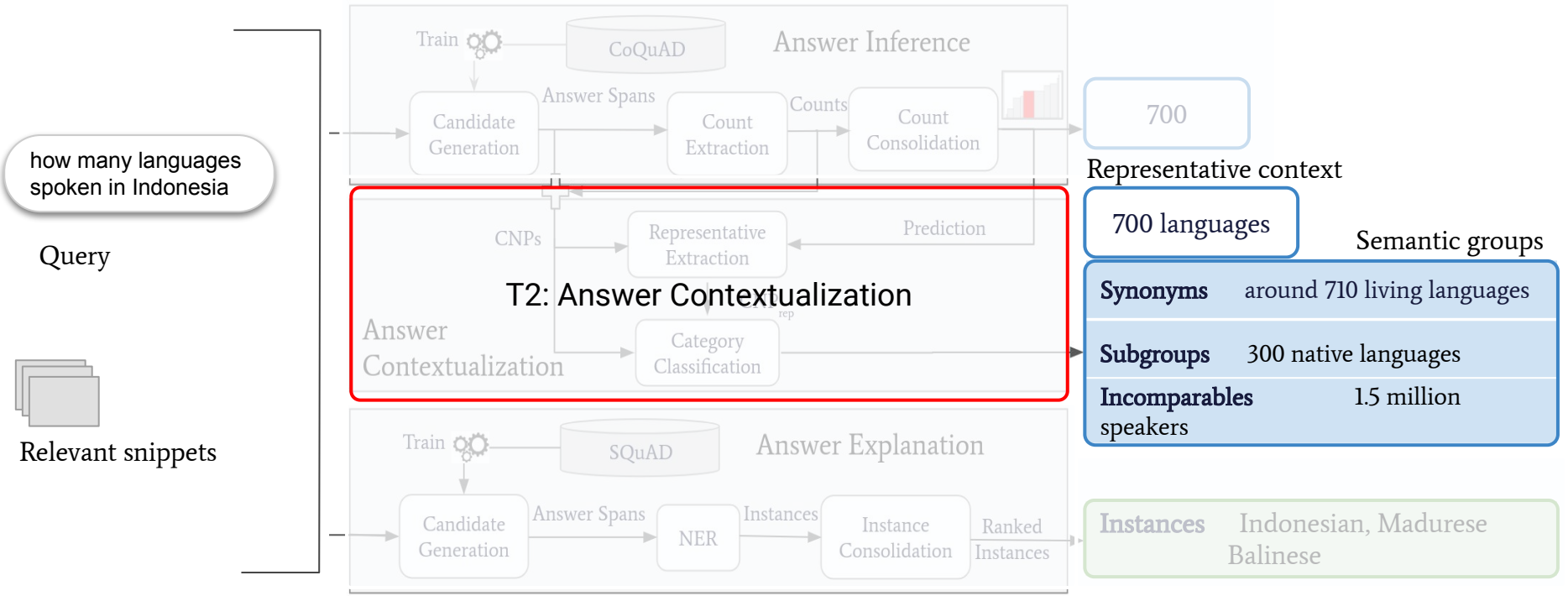
300	0.94	700	0.91	710	0.96	1,500,000	0.61

Strategies

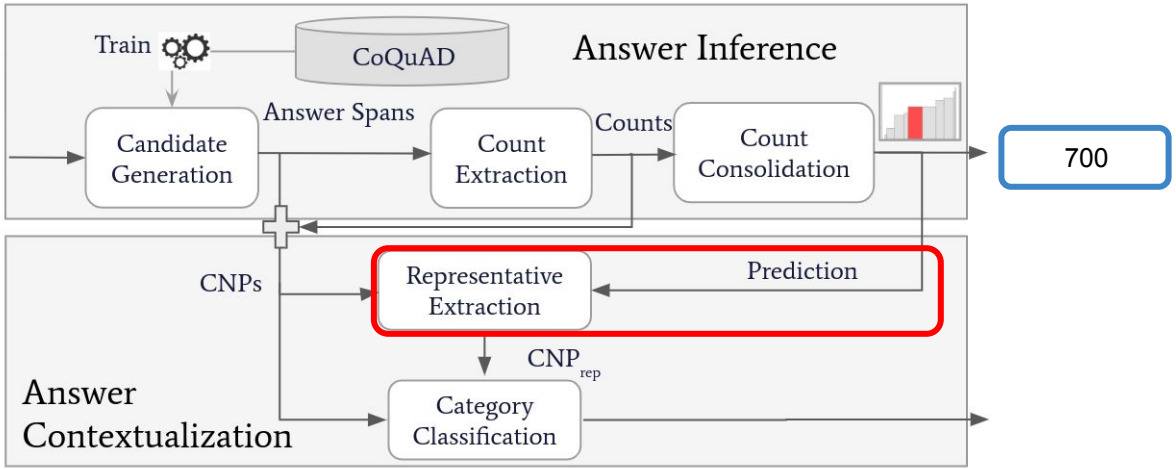
- Median
- Most Frequent
- Most Confident
- Weighted Median

Contributions: RQ2

Count Question answering with Explanatory evidence

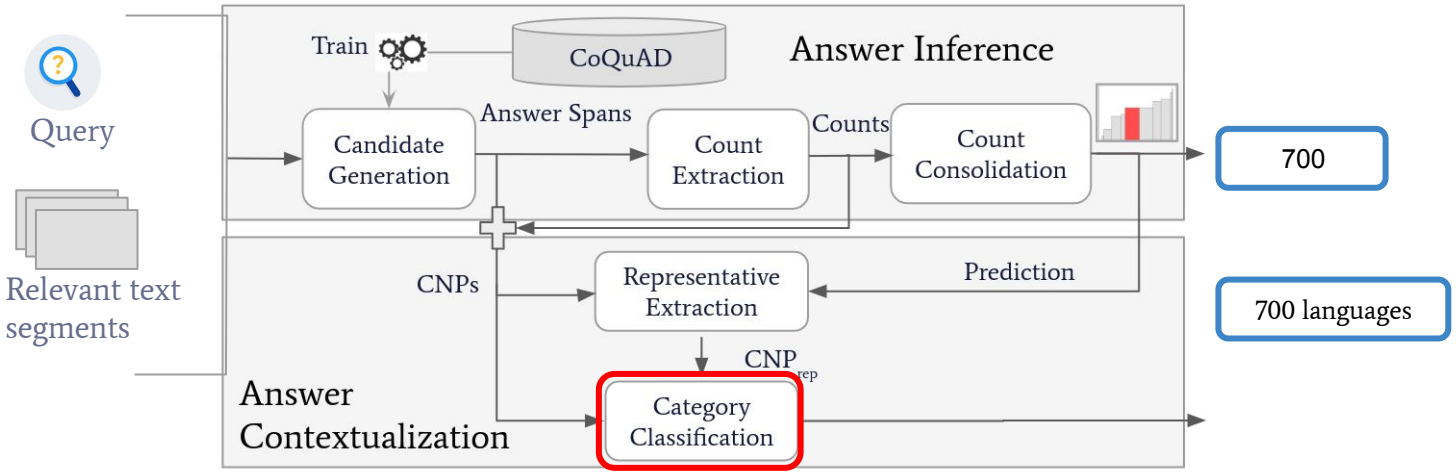


Contributions: RQ2: Answer Contextualization

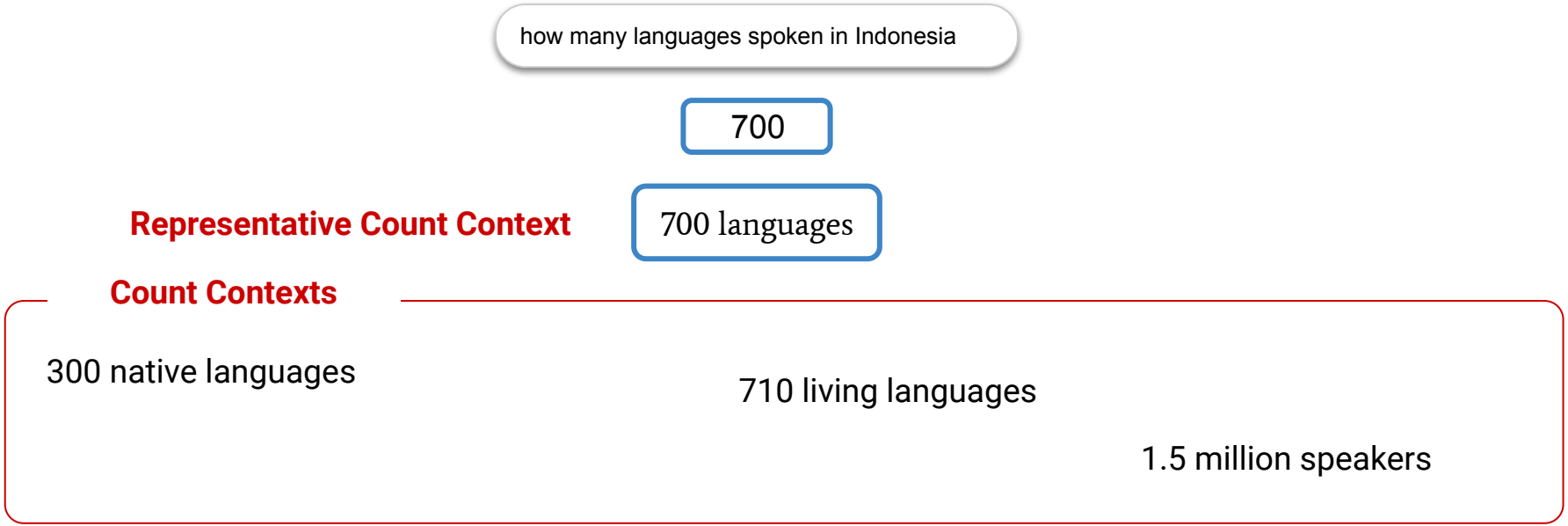


Contributions: RQ2: Answer Contextualization

Contributions: RQ2: Answer Contextualization



Contributions: RQ2: Answer Contextualization



Semantic groups of count contexts w.r.t. the representative count context

- **Numeric distance** of the counts
- **Cosine similarity** of the vector embeddings of count contexts

Contributions: RQ2: Answer Contextualization

how many languages spoken in Indonesia

700

Representative Count Context

700 languages

300 native languages

Subgroups
High cos. similarity
High numeric distance (<)

710 living languages

Synonyms
High cos. similarity
Low numeric distance

1.5 million speakers

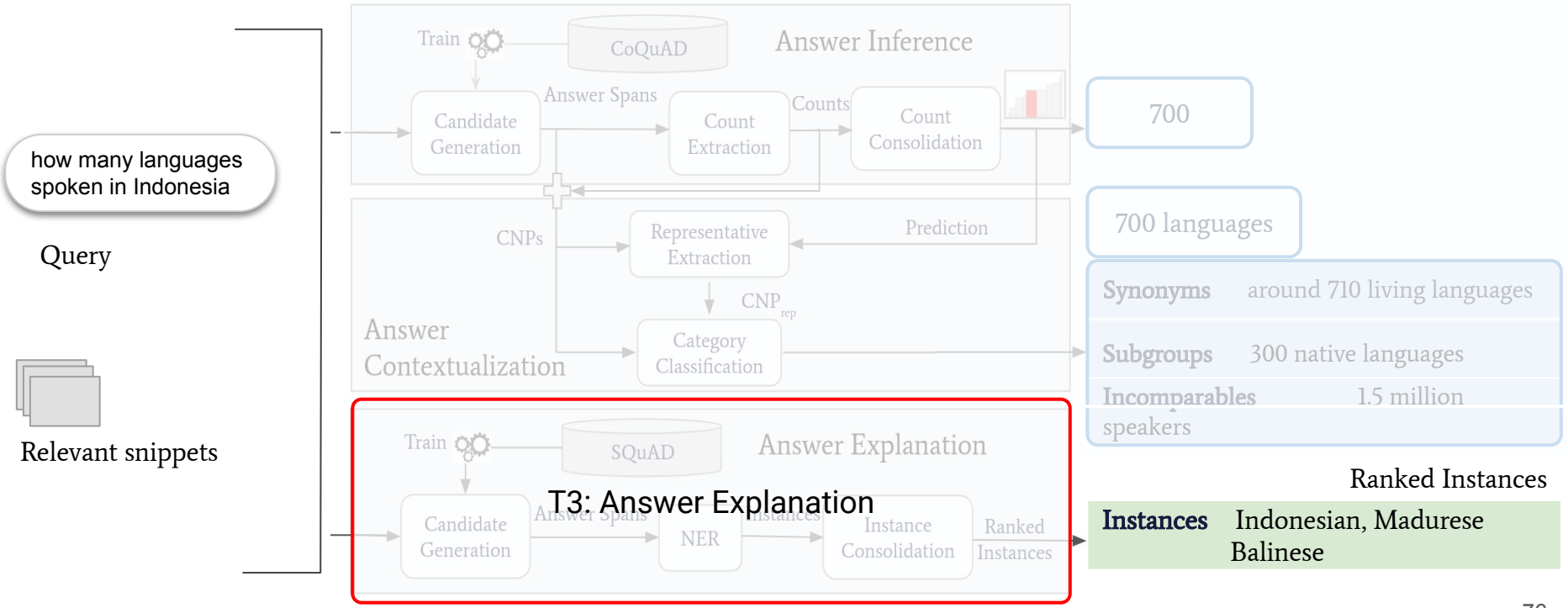
Incomparables
Low cos. similarity
or
High cos. similarity
High numeric distance (>)

Semantic groups of count contexts w.r.t. the representative count co

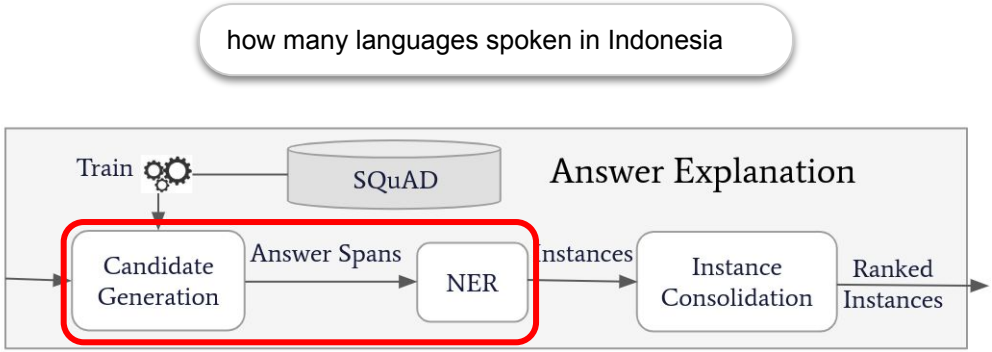
- **Numeric distance** of the counts
- **Cosine similarity** of the vector embeddings of count contexts

Contributions: RQ2

Count Question answering with Explanatory evidence



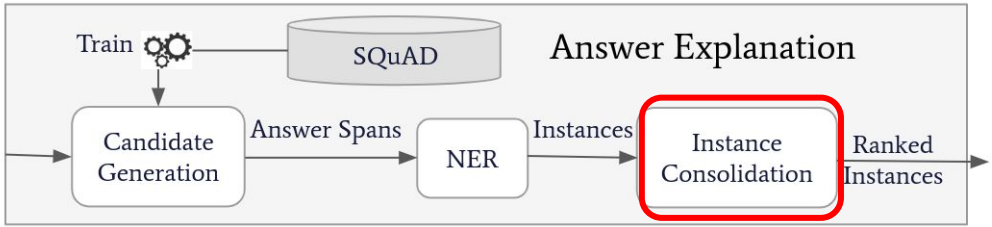
Contributions: RQ2: Answer Explanation



Snippets (Candidate Answer Spans)	→	**Instances (named-entities)**
Madurese and Indonesian are spoken, ..		Madurese
		Indonesian
Other commonly used languages are Balinese, ..		Balinese

Contributions: RQ2: Answer Explanation

how many languages spoken in Indonesia



Instances
Madurese
Indonesian
Balinese

Madurese 0.97

Indonesian 0.97

Balinese 0.78

Strategies

- No consolidation
- Context Frequency
- Summed Confidence
- Type Compatibility

Contributions: RQ2: CoQEx

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Demo

Contributions: RQ2: Results

Baselines

QAnswer [Diefenbach et al. (2019)] QA over KB

GoogleSDA QA over the Web via search-engine direct answer

Contributions: RQ2: Results

Baselines

QAnswer [Diefenbach et al. (2019)] QA over KB

GoogleSDA QA over the Web via search-engine direct answer

Metrics (Answer Inference)

Relaxed Precision (RP) answer is within ± α of GT

Coverage (Cov) fraction of non-empty answers

P/C RP vs Cov tradeoff

Metrics (Answer Explanation)

Mean Average Precision (MAP) fraction of relevant instances

Average Recall (AR) fraction of ground-truth entities returned

Hit@k fraction of queries with ≥ 1 relevant instances in the top-k

Mean Reciprocal Rank (MRR) inverse rank of the 1st relevant instance

Contributions: RQ2: Results

Answer Inference

CoQEx provides better trade-off between relaxed precision and coverage.

System	CoQuAD			LCQuAD_{count}			Stresstest			NaturalQuestions		
	RP	Cov	P/C	RP	Cov	P/C	RP	Cov	P/C	RP	Cov	P/C
QAnswer [Diefenbach et al.(2019)]	6.6	96.2	12.4	45.0	96.1	**61.3**	9.0	100	16.5	12.5	98.8	22.1
GoogleSDA	93.2	18.3	30.6	44.4	8.6	14.4	79.3	29.0	42.4	94.4	22.6	36.4
CoQEx	37.7	84.7	**52.2**	13.6	49.3	21.3	43.6	91.6	**59.1**	43.0	91.6	**58.5**

System	KG (50)			Snippet (172)			NDA (100)		
	RP	Cov	P/C	RP	Cov	P/C	RP	Cov	P/C
QAnswer [Diefenbach et al.(2019)]	12.2	98.0	21.7	4.1	97.0	8.0	8.2	94.0	15.1
GoogleSDA	100	100	**100**	75.0	2.3	4.5	40.0	5.0	8.8
CoQEx	23.1	98.0	37.4	45.3	85.8	**59.3**	31.9	76.3	**45.0**

by CoQuAD GT source

CoQEx shines in queries with no direct answers or queries answerable by featured snippets.

Contributions: RQ2: Results

Answer Explanations

Baselines perform well on KG-answerable queries
GoogleSDA returns **no instances** for snippet-answerable queries.

System	MAP@1	MAP@5	MAP@10	AR@1	AR@5	AR@10	Hit@10	MRR
CoQuAD (142 queries)								
QAnswer [Diefenbach et al.(2019)]	8.5	9.3	9.6	2.9	6.5	8.4	19.7	0.118
GoogleSDA	**14.8**	**12.8**	**10.6**	**4.8**	**13.7**	**14.3**	23.2	0.185
CoQEx	12.0	11.7	11.0	2.3	9.3	12.7	**37.3**	**0.200**
KG (50 queries)								
QAnswer [Diefenbach et al.(2019)]	20.0	21.3	22.0	6.1	14.2	18.5	38.0	0.250
GoogleSDA	**42.0**	**36.4**	**30.0**	**13.5**	**38.9**	**40.7**	**66.0**	**0.526**
CoQEx	14.0	13.7	12.9	3.8	13.0	18.4	42.0	0.233
Snippet (92 queries)								
QAnswer [Diefenbach et al.(2019)]	2.2	2.8	2.9	1.2	2.4	3.0	9.8	0.046
GoogleSDA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
CoQEx	**10.9**	**10.6**	**10.0**	**1.5**	**7.3**	**9.7**	**34.8**	**0.182**

by CoQuAD GT source

CoQEx shines in snippet-answerable queries.

Contributions: RQ2: User Study

Annotator Precision on Answer Inference

Class	Only Count	+Instances	+CNPs	+Snippet	All
Correct	73	63	78	75	**88**
Incorrect	28	45	40	**53**	45
Both	55	56	63	66	**71**

Annotator precision (in %age)

User can better distinguish between correct and incorrect system answers, especially incorrect, with the help of different forms of CoQEx explanations.

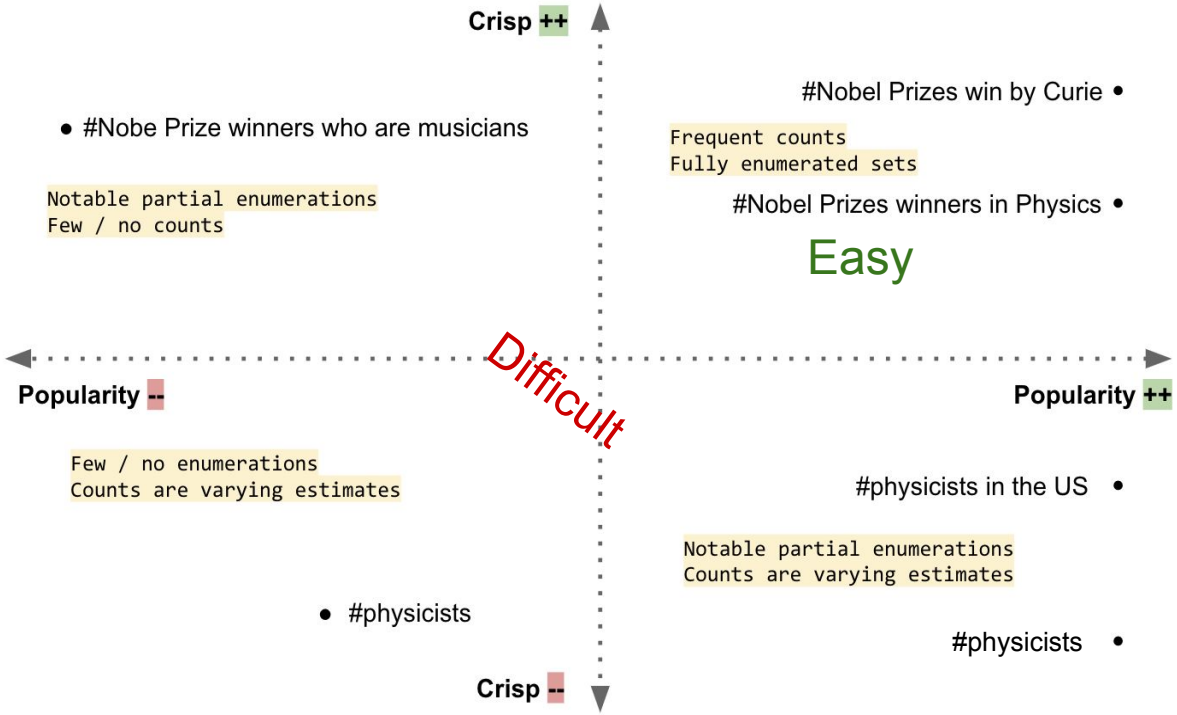
2. Contributions

RQ4: Cardinality Estimation

GPT4-o and DALL-E AI

Contributions: RQ4

RQ4: How to make traceable cardinality estimations in the age of LLMs?



how many physicists are there?

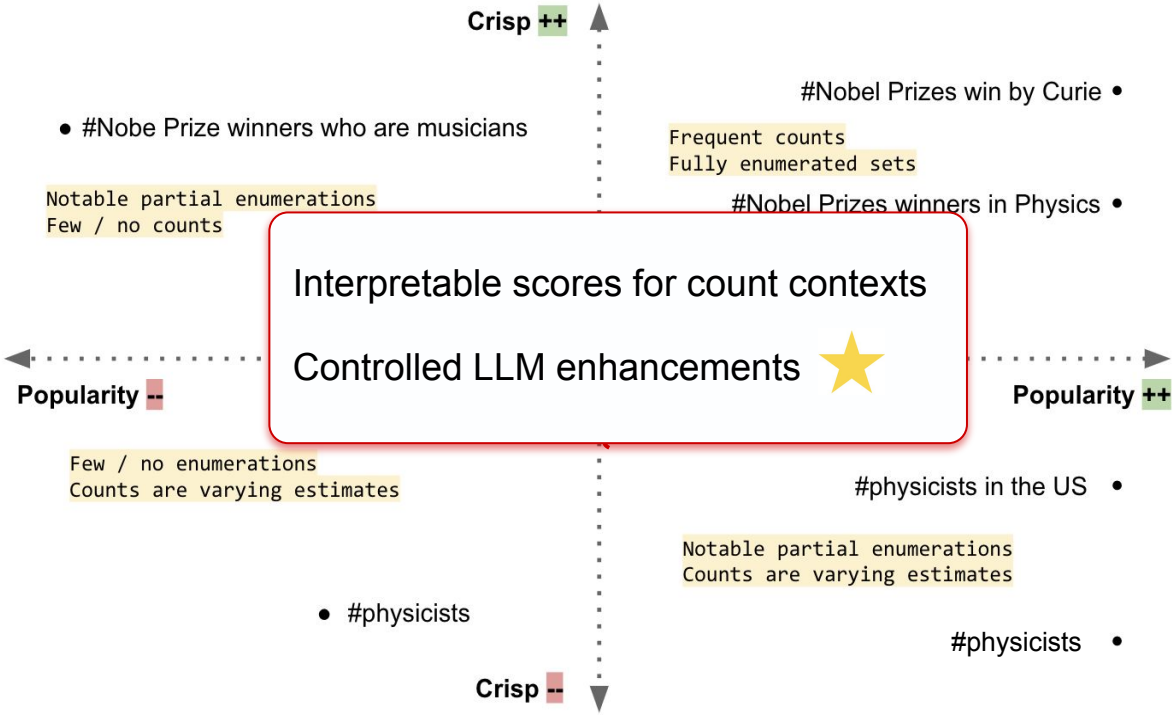
It is difficult to give an exact number of physicists ... However, as of 2021, there are estimated to be over 130,000 physicists globally according to data from the American Physical Society.

how many physicists are there?

It is difficult to provide an exact number of physicists worldwide as the number is constantly changing due to new individuals entering the field and others leaving. However, according to the American Physical Society, there are over 50,000 members in their organization alone. When considering physicists globally, the number is likely in the hundreds of thousands.

Contributions: RQ4

RQ4: How to make traceable cardinality estimations in the age of LLMs?



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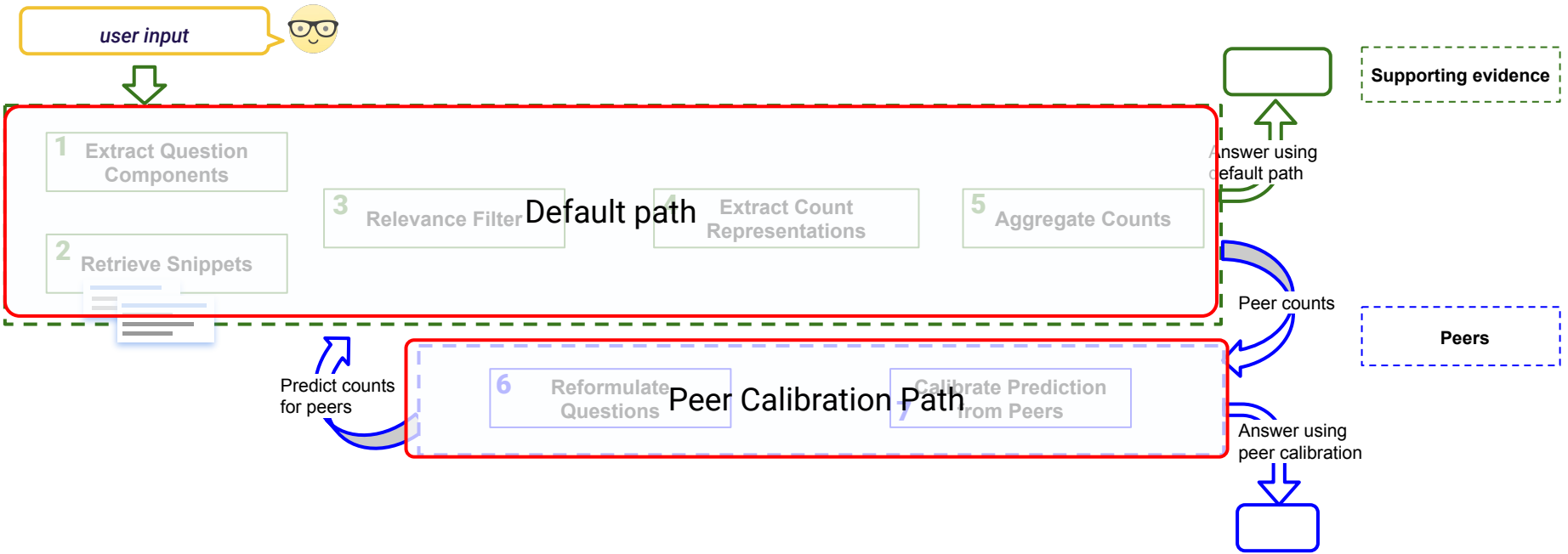
Contributions: RQ4: CardiO *WWW 2024*

Cardinality Predictor from **O**nline Sources



Contributions: RQ4: Default Path

Sentence-level relevance of counts

Cos. Sim. question and snippet	
.. 17,000 Artificial Intelligence companies	0.85
.. ~~startups in 46 US states ..~~	0.43
.. startups .. approx. 14,000 .. in AI in US..	0.92
.. 524 startups founded in US in 2022.	0.69

LLM Filter
✓ .. 17,000 Artificial Intelligence companies
~~.. startups in 46 US states ..~~
✓ .. startups .. approx. 14,000 .. in AI in US..
✓ .. 524 startups founded in US in 2022.

Contributions: RQ4: Count Representation

Track context of count in three levels: type, sentence, snippet

4 Extract Count Representations

5 Aggregate Counts

Answer using default path

Supporting evidence

Extract with using dependency parsers or LLMs

Sentence	count	type	sentence	snippet
.. 17,000 Artificial Intelligence companies	17,000	Artificial Intelligence companies		
.. startups .. approx. 14,000 .. in AI in US..	14,000			
.. 524 startups founded in US in 2022.	524	startups		

Contributions: RQ4: Count Aggregation

Relevance and consistency

Relevance of source (sentence, snippet) to question
Relevance of context type to answer type (*AI startups*)
and
nearest-neighbour consistency

5 Aggregate Counts

17,000 Artificial Intelligence companies

startups .. 14,000 .. in AI

Supporting evidence

Count Representation (c)

count	type	sentence	snippet
17,000	Artificial Intelligence companies		
14,000			
524	startups		

Consistency(c)

$$\beta R(c) + (1 - \beta) R_{cons}(c)$$

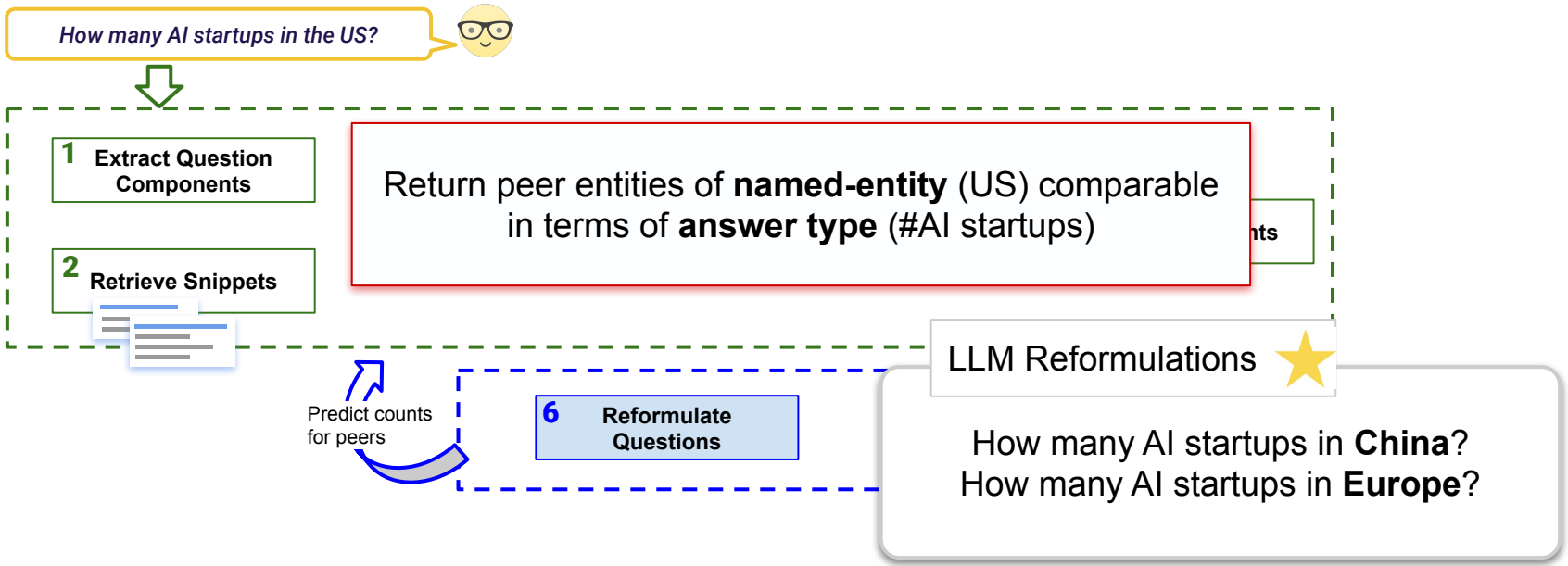
524 startups

dropped

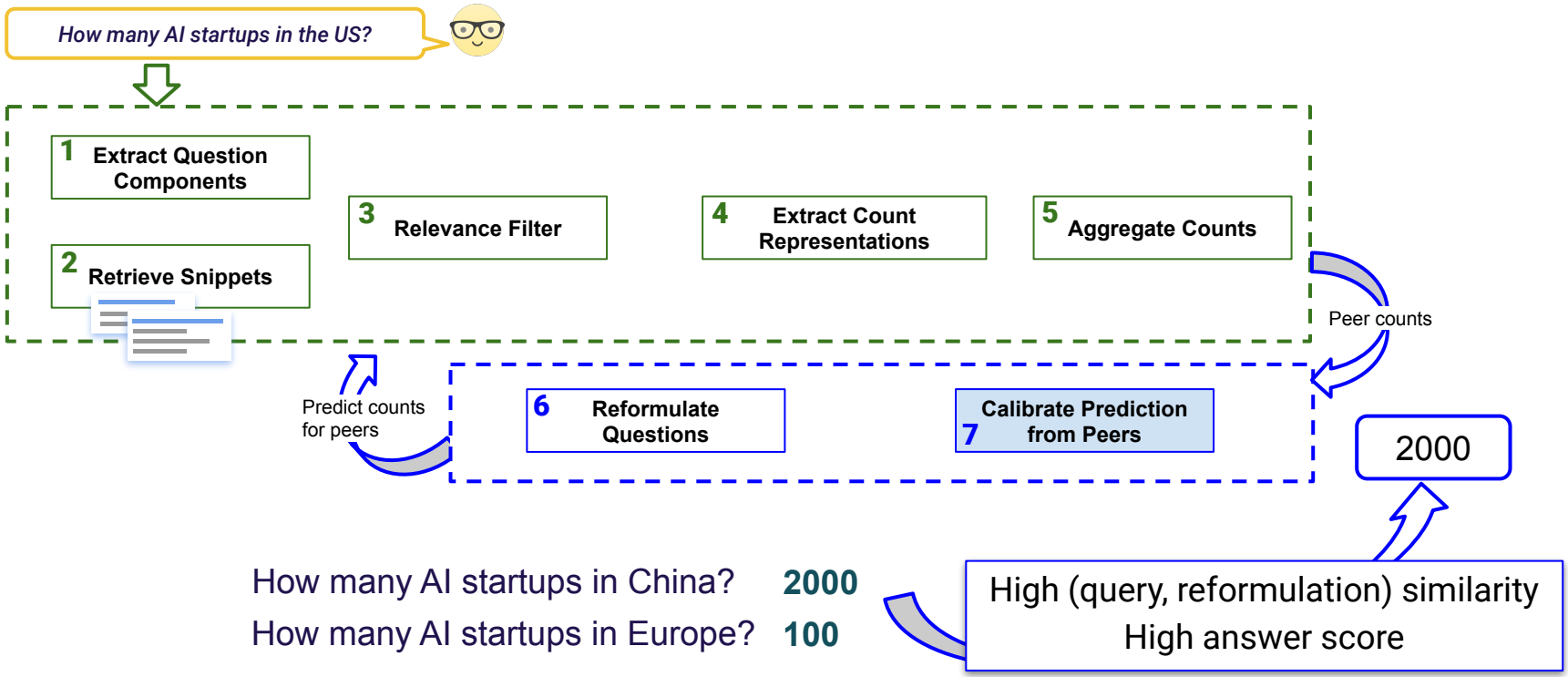
Relevance score of the count repr.

Combined relevance scores of k-nearest count repr.

Contributions: CardiO: Peer Calibration Path



Contributions: CardiO: Peer Calibration Path



Contributions: RQ4: Results

Metrics

Order-of-magnitude precision and recall (OMP, OMR)

Baselines

CoQEx

Llama2

GPT3.5

Contributions: RQ4: Results

Metrics

Order-of-magnitude precision and recall (OMP, OMR)

Baselines

CoQEx	Fully traceable, Model parameters ~100M	
Llama2	7B, 70B	Pretrained, Finetuned
GPT3.5	~100B	Finetuned
	Model parameters	Model Training

Contributions: RQ4: Results

Metrics

Order-of-magnitude precision and recall (OMP, OMR)

Baselines

CoQEx	Fully traceable, Model parameters ~100M	
Llama2	0-shot:	None
GPT3.5	Snippet-augmented:	Limited
	Traceability	

Contributions: RQ4: Results

Benchmarks

Cardinality Questions (CQ): 500 high-quality annotated questions

Question characteristics: popularity, specificity, presence of named-entity
Ground-truth characteristics: exact/estimate, direct/aggregated, time variance

CoQuAD: 312 questions

Natural Questions (NQ): 84 questions

Contributions: RQ4: Results

CardiO vs. LLM

- CardiO at par / better than Llama models in 0-shot setting.
- CardiO ahead of snippet-augmented Llama models in recall.

Answer Traceability	Method	CQ (n=500)			NQ (n=84)			CoQuAD (n=312)		
		EP	OMP	OMR	EP	OMP	OMR	EP	OMP	OMR
Not possible	0-shot LLAMA2-7B-chat	0.056	0.578	0.560	0.250	0.695	0.662	0.137	0.584	0.547
	0-shot LLAMA2-70B	0.113	0.670	0.521	0.288	0.725	0.630	0.190	0.692	0.548
	0-shot LLAMA2-70B-chat	0.079	0.653	0.631	0.325	0.775	0.738	0.220	0.646	0.621
	0-shot GPT3.5	0.133	0.716	0.689	0.438	0.797	0.759	0.273	0.724	0.689
Medium	Snippets + LLAMA2-7B-chat	0.213	0.640	0.553	0.289	0.674	0.610	0.224	0.635	0.572
	Snippets + LLAMA2-70B	0.242	0.723	0.567	0.338	0.723	0.611	0.320	0.743	0.581
	Snippets + LLAMA2-70B-chat	0.278	0.743	0.728	0.494	0.838	0.808	0.302	0.749	0.715
	Snippets + GPT3.5	0.303	0.825	0.751	0.548	0.834	0.724	0.381	0.815	0.726
High	CoQEx [Ghosh et al.(2022a)]	0.175	0.631	0.577	0.329	0.665	0.626	0.266	0.696	0.611
	CardiO (vanilla)	0.192	0.659	0.659	0.298	0.661	0.661	0.228	0.618	0.618

Contributions: RQ4: Results

CardiO vs. LLM

- CardiO at par / better than Llama models in 0-shot setting.
- CardiO ahead of snippet-augmented Llama models in recall.
- Questions where CardiO outperforms Llama w. snippets:
  - no named-entity
  - fuzzy entity set

Contributions: RQ4: Results

CardiO vs. LLM

- CardiO at par / better than Llama models in 0-shot setting.
- CardiO ahead of snip
- Questions where Car
  - no named-entity
  - fuzzy entity set

how many AI researchers are there

Llama2-70B w. snippets

Ground truth: 300,000

Generated text: *"According to the article, there are approximately 300 full-time technical AI safety researchers, 100 full-time non-technical AI safety researchers, and 400 AI safety researchers in total today. ..(one more explanation sentence)"*

Extracted counts: [300, 100, 400] (we evaluate the first count)

CardiO

CardiO prediction: 300,000

Source context: just 300,000 AI researchers

Source snippet: blueTencent says there are only 300,000 AI engineers worldwide, but ... According to the study, compiled by the Tencent Research Institute, there are just 300,000 "AI researchers and practitioners" worldwide, but the "market demand" is for millions of roles.

Contributions: RQ4: Results

LLM enhancements in CardiO

- Sentence filter and peer calibration provide minimal improvements
- Count extraction decreases overall performance

Method	CQ (n=500)			NQ (n=84)			CoQuAD (n=312)		
	EP	OMP	OMR	EP	OMP	OMR	EP	OMP	OMR
CoQEx [Ghosh et al.(2022a)]	0.175	0.631	0.577	0.329	0.665	0.626	0.266	0.696	0.611
CardiO (vanilla)	0.192	0.659	0.659	0.298	0.661	0.661	0.228	0.618	0.618
+ LLM Sentence filter	0.191	0.663	0.653	0.293	0.657	0.634	0.229	0.657	0.634
+ LLM Count extraction	0.174	0.571	0.571	0.298	0.661	0.661	0.205	0.601	0.601
+ Peer calibration	0.190	0.657	0.657	0.310	0.654	0.654	0.234	0.623	0.623

Contributions: RQ4: Results

Aggregation based on neighbours

- No significant performance improvement over only relevance
- No performance degradation → serve as reliable supporting evidence

Method	CQ (n=500)			NQ (n=84)			CoQuAD (n=312)		
	EP	OMP	OMR	EP	OMP	OMR	EP	OMP	OMR
CoQEx [Ghosh et al.(2022a)]	0.175	0.631	0.577	0.329	0.665	0.626	0.266	0.696	0.611
CardiO (vanilla)	0.192	0.659	0.659	0.298	0.661	0.661	0.228	0.618	0.618
+ Consistent aggregation	0.186 (±0.064)	0.653 (±0.023)	0.653 (±0.023)	0.274	0.660	0.660	0.240	0.642	0.642

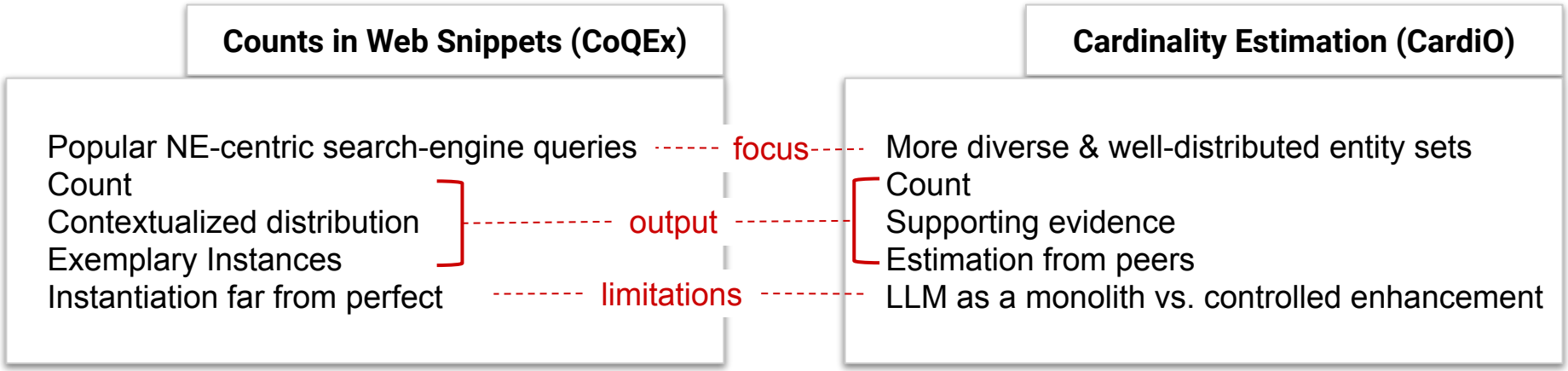
3. Summary

Summary

- Count information can expressed as **a cardinality** or **enumerations**
- Knowledge on the Web is in **explicit** and **latent** format

Summary

- Count information can expressed as **a cardinality** or **enumerations**
- Knowledge on the Web is in **explicit** and **latent** format



4. Limitations & Future Work

Limitations

* Training and evaluation data
    - Crowd-sourced dataset → quality control
    - Semi-automated dataset → popularity bias
    - Expert annotated dataset → scalability issues

Limitations

- Training and evaluation data
  - Crowd-sourced dataset → quality control
  - Semi-automated dataset → popularity bias
  - Expert annotated dataset → scalability issues
- Predicting strict bounds is hard
  - Mathematical relations (<,>,~,=) extracted but unused
  - Semantic grouping could be principled

how many AI startups?

more than 1000 startups upper bound?
500 GenAI companies in US in 2020 lower bound?

Future Work

- Numbers are yet more tokens for LLMs

  Supervised training to extract structured count representations.

  Counting capability is underexplored

- Reasoning in LLMs is not well-understood

  Focus on explainability, traceability, verification.

- Count information as exploratory search

  Popular subgroups / peers to estimate bounds.

- Beyond counts of named-entities

  Numbers in sports / financial analysis.

5. Conclusion

Conclusion

Counts in KBs (CounQER)

counquer.mpi-inf.mpg.de/spo

Uncovering Hidden Semantics of Set Information in Knowledge Bases
Shrestha Ghosh, Simon Razniewski, Gerhard Weikum. *Journal of Web Semantics 2020.*

CounQER: A System for Discovering and Linking Count Information in Knowledge Bases
Shrestha Ghosh, Simon Razniewski, Gerhard Weikum. *System demonstration at ESWC 2020.*

Counts in Web Snippets (CoQEx)

nlcounquer.mpi-inf.mpg.de

Answering Count Queries with Explanatory Evidence
Shrestha Ghosh, Simon Razniewski, Gerhard Weikum. *SIGIR 2022.*

CoQuAD

Answering Count Questions with Structured Answers from Text
Shrestha Ghosh, Simon Razniewski, Gerhard Weikum. *Journal of Web Semantics 2023.*

CoQEx: Entity Counts Explained
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Cardinality Comparison

Class Cardinality Comparison as a Fermi Problem
Shrestha Ghosh, Simon Razniewski, Gerhard Weikum. *Web Conference 2023.*

Cardinality Estimation (CardiO)

CardiO: Predicting Cardinality from Online Sources
Shrestha Ghosh, Simon Razniewski, Damien Graux, Gerhard Weikum. *Web Conference 2024.*

CQ

Conclusion

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CoQuAD

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