

RAG Exam Generation

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Natural Language Processing

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Project overview

Steps of the project:

- Explore existing solutions and prepare literature review
- EDA of the datasets that can be used
- Create a RAG system capable of retrieving question-answer pairs given context
- **Validate approach**

Datasets Used:

- **SQuAD** (Stanford Question Answering Dataset) – A widely-used benchmark dataset for reading comprehension.
- **NewsQA** – A dataset focused on question answering over news articles.
- **HotpotQA** – A dataset designed for multi-hop question answering.

Models and Tools Used

Models:

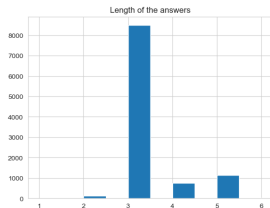
- **GPT-4o**
- **Llama 3.1**

Tools:

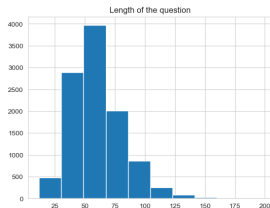
- **LangChain** – A framework designed for building applications that leverage LLMs (Large Language Models) to create pipelines, manage prompts, and interact with external tools.

EDA of SQUAD dataset

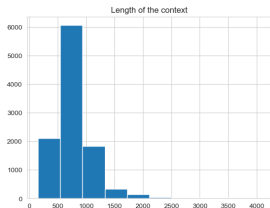
Validation split consists of 10570 question-answer-context triples.



Answer Length
(characters)



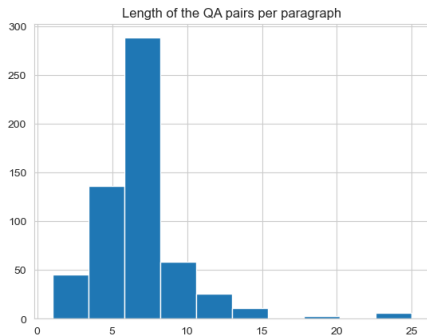
Question Length
(characters)



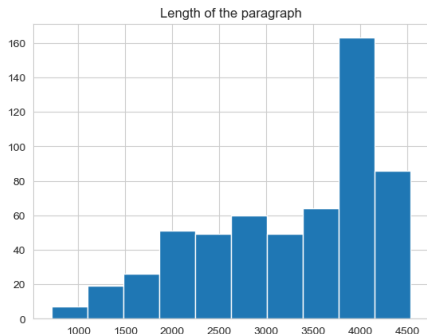
Context Length
(characters)

EDA of NewsQA dataset

Validation split consists of 574 question-answer context triples



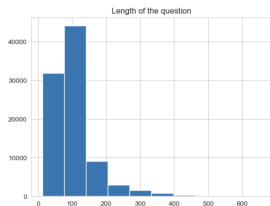
Distribution of the length of the question-answer pairs (number of characters)



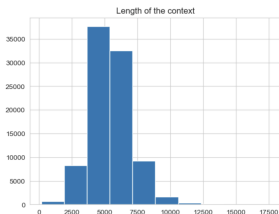
Distribution of the length of the context (number of characters)

EDA of Hotpot QA dataset

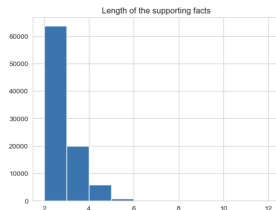
Validation split consists of 90447 question-answer context triples.



Distribution of the length of questions
(number of characters)



Distribution of the length of contexts
(number of characters)



Distribution of the length of answers
(number of characters)

Generated Questions and Answers by GPT-4

Question: What year did Tesla die?

Generated Answer: Tesla died in 1943.

Correct Answers: ['1943', '1943', '1943']

Figure: GPT-4 - generated answer to the question based on the context provided

Question: Where was Tesla's property sent?

Generated Answer: Tesla's property was sent to Belgrade.

Correct Answers: ['Belgrade', 'Belgrade', 'Belgrade']

Figure: GPT-4 - generated answer to the question based on the context provided

Generated Questions and Answers by GPT-4

Context: question='Which series were featured on the first Doctor Who soundtrack?' example_correct_answers=['the first two series', 'the first two series', 'the first two'] context='Six soundtrack releases have been released since 2005. The first featured tracks from the first two series, the second and third featured music from the third and fourth series respectively. The fourth was released on 4 October 2010 as a two disc special edition and contained music from the 2008–2010 specials (The Next Doctor to End of Time Part 2). The soundtrack for Series 5 was released on 8 November 2010. In February 2011, a soundtrack was released for the 2010 Christmas special: "A Christmas Carol", and in December 2011 the soundtrack for Series 6 was released, both by Silva Screen Records.'

Generated Question: What is the release date of the soundtrack for Series 5, and which company released the soundtracks for the 2010 Christmas special and Series 6?

Figure: GPT-4 - generated question based on the context provided

Generated Questions and Answers by GPT-4

```
Context: context="The Black Death is thought to have originated in the arid plains of Central Asia, where it then travelled along the Silk Road, reaching Crimea by 1343. From there, it was most likely carried by Oriental rat fleas living on the black rats that were regular passengers on merchant ships. Spreading throughout the Mediterranean and Europe, the Black Death is estimated to have killed 30–60% of Europe's total population. In total, the plague reduced the world population from an estimated 450 million down to 350–375 million in the 14th century. The world population as a whole did not recover to pre-plague levels until the 17th century. The plague recurred occasionally in Europe until the 19th century." question=None
Generated Question: Where did the Black Death originate?
Choices: ['Central Asia', 'Crimea', 'Mediterranean', 'Europe']
Correct Answer: 0
```

Figure: GPT-4 - generated closed-ended question based on the context provided

Generated Questions and Answers by Llama 3.1

Question: Which sitcom ended its broadcast run for ABC in 1983?

Generated Answer: Laverne & Shirley.

Correct Answers: ['Laverne & Shirley', 'Laverne & Shirley', 'Laverne & Shirley']

Figure: Llama 3.1 - generated answer to the question based on the context provided

Question: What is the minimum required if you want to teach in Canada?

Generated Answer: A post-secondary degree (Bachelor's Degree) is required.

Correct Answers: ["a post-secondary degree Bachelor's Degree", "a post-secondary degree Bachelor's Degree", "post-secondary degree Bachelor's Degree"]

Figure: Llama 3.1 - generated answer to the question based on the context provided

Generated Questions and Answers by Llama 3.1

Context: Later in life, Tesla made claims concerning a "teleforce" weapon after studying the Van de Graaff generator. The press variably referred to it as a "peace ray" or death ray. Tesla described the weapon as capable of being used against ground-based infantry or for anti-aircraft purposes.

Generated Question: What was the name given by the press to Tesla's proposed energy-based weapon?

Figure: Llama 3.1 - generated question based on the context provided

Questions and answers by LLMs

- Can LLM generate the answer to the question based on the context provided?
- Can LLM grade the answer to the question based on the context provided and the example answer?
- Does LLM actually grade an answer or hallucinate it?

Process of asking and grading a question

- $\text{Answer} = \text{Context} + \text{Question} [+ \text{Choices}]$
- $\text{Grade} = \text{Context} + \text{Question} [+ \text{Choices}] + \text{Answer}$
- $\text{Grade} \in [0, 5]$

GPT 4o results

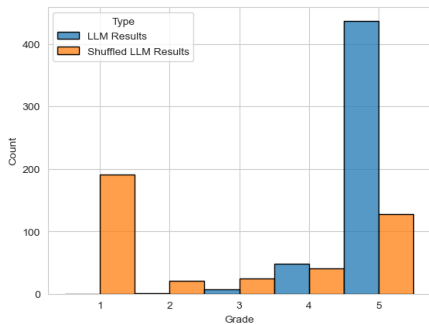


Figure: GPT-4o SQUAD: Grading answers to questions vs grading shuffled answers to questions

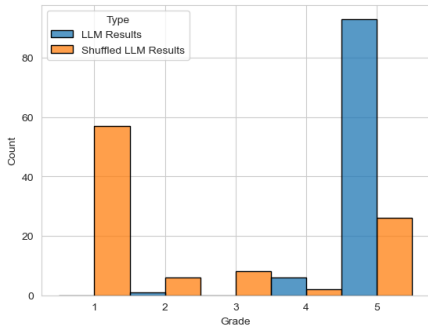


Figure: GPT-4o NewsQA: Grading answers to questions vs grading shuffled answers to questions

GPT 4o results

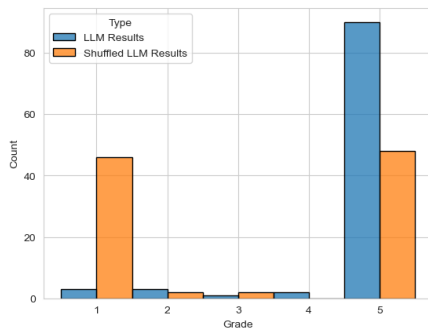


Figure: GPT-4o HotpotQA: Grading answers to questions vs grading shuffled answers to questions

LLama 3.1 results

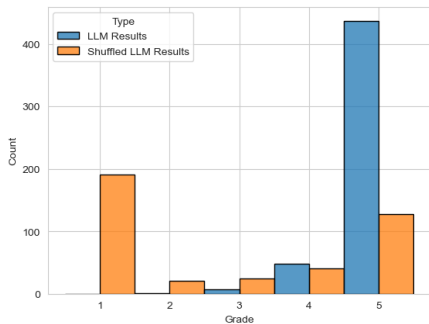


Figure: LLaMa 3.1 SQUAD: Grading answers to questions vs grading shuffled answers to questions

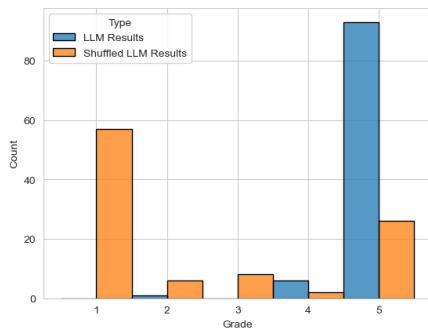


Figure: LLaMa 3.1 NewsQA: Grading answers to questions vs grading shuffled answers to questions

LLama 3.1 results

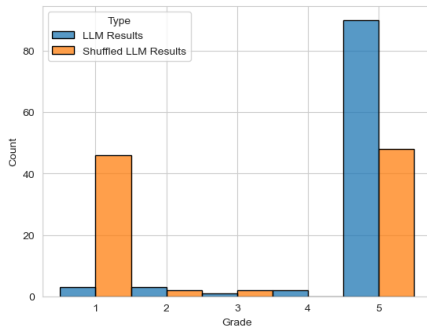


Figure: LLaMa 3.1 HotpotQA:
Grading answers to questions vs
grading shuffled answers to questions

Content Uniqueness (CU) - Definition

What it measures:

- CU quantifies the uniqueness of the answer bigrams in comparison to:
 - Repeated bigrams within the answer itself (*self-redundancy*).
 - Bigrams shared between the answer and the question.

How it works:

- The metric computes the proportion of non-redundant bigrams in the answers after accounting for bigrams that:
 - Appear more than once in the answers.
 - Are present in the questions.

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Content Uniqueness (CU) - Uniqueness

Interpretation:

- A high CU value (close to 1) suggests that the answer content is highly unique:
 - Limited overlap with the question.
 - Minimal repetition within the answer itself.
- A low CU value (close to 0) suggests that the answer content is either:
 - Highly redundant (repeats bigrams frequently).
 - Shares significant overlap with the question.

What Does DSI Measure?

Definition:

- DSI quantifies the average pairwise cosine dissimilarity ($1 - \text{cosine similarity}$) between token embeddings within a text (e.g., sentences or answers).

Interpretation:

• High DSI:

- Indicates a lower degree of semantic cohesion.
- Words (tokens) are semantically less similar, reflecting diverse or less contextually focused content.

• Low DSI:

- Indicates a higher degree of semantic cohesion.
- Words (tokens) are semantically more similar, suggesting repetitive or highly focused content.

How Does DSI Work?

Steps:

- **Tokenization and Hidden States Extraction:**

- The text is segmented into sentences using a tokenizer.
- Each sentence is tokenized into words and converted into embeddings using hidden states from layers 6 and 7 of a pre-trained BERT model (`bert-large-uncased`).

- **Cosine Dissimilarity Calculation:**

- For each pair of embeddings within the text (ignoring diagonal pairs and duplicates), the cosine dissimilarity is computed.

- **Aggregation:**

- The average dissimilarity across all token pairs forms the DSI score for the text.

What Does the DSI Metric Say?

High DSI Values:

- Texts are more diverse in semantic content.
- Indicates rich, varied language usage or a lack of focus in structure.
- Example: Creative, varied responses in educational datasets.

Low DSI Values:

- Texts are more homogeneous or repetitive.
- May indicate repetitive phrasing, structured responses, or template-like answers.
- Example: Responses following predefined patterns.

D Metric: Measuring Redundancy in Text

What it measures:

- The D Metric calculates the redundancy in a string by measuring how often words repeat relative to the total number of words.

Interpretation:

- **High D values:** Significant repetition of words, indicating low diversity.
- **Low D values:** More unique or diverse word usage.

Metrics in Sentence Analysis: Linguistic Features

General Linguistic Features:

- **CharacterNumber and WordNumber:** Total number of characters and words; basic indicators of text length.
- **CommonWordNumber:** Proportion of common words in text; reflects simplicity of language.
- **UniqueWordNumber:** Count of unique words; indicates vocabulary diversity.

Vocabulary Metrics:

- **TTR (Type-Token Ratio):** Ratio of unique words to total words; shows lexical variety but is sensitive to text length.
- **CTTR (Corrected TTR):** A normalized version of TTR that reduces sensitivity to text length:

$$CTTR = \frac{\text{Unique Word Number}}{\sqrt{2 \cdot \text{Word Number}}}$$

Metrics in Sentence Analysis: Linguistic Features

Redundancy Metric:

- **DMetric:** Measures redundancy in the text by calculating the frequency of word repetition relative to the total word count.

Readability Features:

- **SyllableNumber:** Approximates syllable count for readability calculations.
- **SentenceNumber:** Total number of sentences in the text.
- **MeanSentenceLength:** Average characters per sentence; indicates verbosity and sentence complexity.

Metrics in Sentence Analysis: Readability Features

Advanced Readability Metrics:

- **FRES (Flesch Reading Ease Score):** Measures how easy the text is to read Higher scores mean easier reading (e.g., 90–100: 5th grade, 0–30: College level).
- **FKGL (Flesch-Kincaid Grade Level):** Determines the grade level required to understand text
- **ARI (Automated Readability Index):** Uses characters instead of syllables to assess readability Correlates with grade levels for reading comprehension.

Metrics Overview: Name and Range

Name of Metric	Range
Content Uniqueness (CU)	[0, 1]
Dissimilarity Index (DSI)	[0, 1]
Redundancy Metric (D)	[0, 1]
Character Number	Positive integers
Word Number	Positive integers
Common Word Number	Positive integers
Unique Word Number	Positive integers
Type-Token Ratio (TTR)	[0, 1]
Corrected TTR (CTTR)	[0, 1]
Flesch Reading Ease Score (FRES)	0 to 100
Flesch-Kincaid Grade Level (FKGL)	0 and above
Automated Readability Index (ARI)	0 and above
Mean Sentence Length	Positive integers
Syllable Number	Positive integers
Sentence Number	Positive integers

Metrics Overview: Good Values

Name of Metric	Good Value
Content Uniqueness (CU)	Close to 1: Highly unique
Dissimilarity Index (DSI)	High: Diverse and semantically varied
Redundancy Metric (D)	Low: Minimal word repetition
Character Number	Depends on the use case: Neither too short/long
Word Number	Depends on the use case: Appropriate length
Common Word Number	Moderate: Simplifies text for readability
Unique Word Number	High: Reflects vocabulary diversity
Type-Token Ratio (TTR)	High: High lexical variety
Corrected TTR (CTTR)	High: Balanced lexical diversity
Flesch Reading Ease Score (FRES)	High (e.g., 60–100): Easy to read
Flesch-Kincaid Grade Level (FKGL)	Low (e.g., below 8): Simple, accessible text
Automated Readability Index (ARI)	Low (e.g., below 10): Easy to understand
Mean Sentence Length	Moderate: Indicates concise, clear sentences
Syllable Number	Moderate: Balanced text complexity
Sentence Number	Appropriate to content: Balanced paragraphing

Metrics Overview: Bad Values

Name of Metric	Bad Value
Content Uniqueness (CU)	Close to 0: Highly redundant or overlapping
Dissimilarity Index (DSI)	Low: Repetitive or homogeneous
Redundancy Metric (D)	High: Excessive word repetition
Character Number	Extremely short or excessively verbose
Word Number	Very short or excessively wordy
Common Word Number	Too high: May indicate lack of variety
Unique Word Number	Low: May indicate overuse of certain words
Type-Token Ratio (TTR)	Low: Limited vocabulary
Corrected TTR (CTTR)	Low: Restricted lexical variety
Flesch Reading Ease Score (FRES)	Low (e.g., 0–30): Difficult to read
Flesch-Kincaid Grade Level (FKGL)	High (e.g., 12+): Complex, advanced text
Automated Readability Index (ARI)	High (e.g., 15+): Challenging text
Mean Sentence Length	High: Verbose or overly complex sentences
Syllable Number	High: Overly complex words, harder to read
Sentence Number	Too low or too high: May suggest poor structure

Questions 1 to 3

What is the primary difference between syntactic analysis and semantic analysis in the context of natural language processing?

What are the major tasks involved in natural language processing, and how is data typically collected for these tasks?

What is lemmatization and how does it differ from other techniques for reducing words to their normalized form?

Questions 4 and 5

What is the main difference between stemming and lemmatization in terms of their approach to reducing words to their base form?

What is the difference between anaphora resolution and the more general task of coreference resolution, and how does the concept of "bridging relationships" fit into coreference resolution?

CU, CU2, and DSI metrics

Index	CU	CU2	DSI
0	0.64	0.38	0.7776
1	0.83	0.58	0.7980
2	0.88	0.63	0.8091
3	0.76	0.33	0.7699
4	0.93	0.62	0.8210
5	0.84	0.62	0.8263
6	0.82	0.63	0.8066
7	0.92	0.50	0.8147
8	0.56	0.42	0.8201
9	0.52	0.32	0.7893
Mean	0.77	0.51	0.799
Variance	0.02	0.02	0.0004

Table: First 10 rows of the data with mean and variance.

Metrics for NLP Questions

Metric	Q1	Q2	Q3	Q4	Q5
Character Number	126	118	111	127	189
Word Number	18	19	18	21	27
Common Word Number	0.5	0.5789	0.6111	0.5714	0.5185
Unique Word Number	16	19	18	19	22
TTR	0.8889	1.0	1.0	0.9048	0.8148
CTTR	2.6667	3.0822	3.0	2.9318	2.9938
DMetric	0.0131	0.0	0.0	0.0095	0.0171
Syllable Number	41	36	31	34	60
Sentence Number	1	1	1	1	1
Mean Sentence Length	126.0	118.0	111.0	127.0	189.0

Thank you for your attention!