

Chapter 10

Building a Ranking System to Enhance Prompt Results

This chapter features the most recent developments to the enterprise version of xLLM described in Part I. The focus here is on returning the best extracts from the corpus, to a prompt or user query, in the context of search and retrieval (**RAG**). These extracts are called **text entities** and may consist of a webpage, part of a webpage, a few text sentences, part of a PDF document, or a JSON entity extracted from the input corpus. Given a prompt and the size of the corpus, their number can be large, thus the need to only return those that are most relevant to the prompt.

Before digging into the **relevancy score** architecture, I introduce important updates to the original enterprise model. I now call it **e-xLLM**, to emphasize its application to enterprise corpuses, and to differentiate it from other versions used for scientific research (see section 10.3), or for clustering and predictions (see chapter 6).

First, I augmented the corporate corpus used in my case study. The new corpus named `repository3.txt`, is on GitHub, [here](#). Text entities from the original corpus have an ID (also called **index**) between 0 and 1000, while the new ones have an ID between 2000 and 4000. I created a new tag to make it easy for the user to know whether some output comes from the original data, or from the augmentation.

Then, I created a library `xllm_enterprise_util.py` to move some code outside the main program `xllm-enterprise-v2.py`. The new program `xllm-enterprise-v2-user.py` imports that library, making it much shorter and easier to understand. But the main upgrade is in `xllm-enterprise-v2-dev.py`. It also imports the same library. Yet, rather than fine-tuning in real time, the goal is to process many prompts with known answer, in bulk. It also includes the relevancy scores discussed earlier, the main topic in this section.

Another improvement is the ability to link tokens from the prompt, to tokens in the corpus, via the `KW_map` table. Sometimes, a user enters a term such as ‘doing business as’, while in the corpus, the corresponding word is ‘dba’. The goal of `KW_map` is to address this issue, to increase **exhaustivity** when returning results. Perhaps the most striking new feature is the introduction of **graph tokens** from the **knowledge graph**, to boost relevancy by leveraging the global **context**. See section 10.1.

Finally, key components built in the first version include **multitokens** and contextual information such as tags, titles, categories, URLs, or related items, in text entities. Contextual elements are detected during the initial crawl and added to the **backend tables**. The scope of the context is global, not local as in most other LLMs. In some instances, contextual elements, for instance **agents**, are created after the initial crawl, typically via a clustering algorithm applied to the corpus. In the end, they are attached to the JSON-like **text entities**, as separate entries from the main text: see an example in Table 2.1. In-memory **nested hashes** and **sub-LLMs** (sometimes called **mixture of experts**), including the **LLM router**, are discussed in Part I.

I now describe the multitokens, as they significantly differ from tokens in other LLM architectures, both in terms on format and usage, as xLLM does not rely on neural networks, has zero weight and no training:

- **Standard multitokens**, for instance ‘San Francisco~real estate’, consist of one or multiple single tokens separated by ‘~’, in this case two single tokens ‘San Francisco’ and ‘real estate’. They may overlap: a same single token can be found in different multitokens, or split into sub-tokens.
- **Contextual multitokens** consist of tokens that are not adjacent in the prompt or corpus, yet found in a same text sub-entity. In this case, the single tokens are separated by `\wedge`, as in ‘San Francisco\wedge real estate’.
- **Graph multitokens** (a new addition) are multitokens found in the contextual fields attached to a text entity, such as sub-category. They start with ‘`_`’ as in ‘`_San Francisco~real estate`’. They are not stored

in the dictionary to save space. Instead, they are found in `hash_ID`, a key-value table where the key is a text entity ID, and the value is a list of multitokens attached to it. See the `update_tables` function in `xllm.enterprise.util.py`.

In the code, I use `gword` to represent graph multitokens.

10.1 Relevancy scores and rankings

The corporate corpus tested here consists of definitions and policies regarding AI integration. It is broken down in text entities (see example in Table 2.1). Each entity is indexed – it has an ID attached to it for easy retrieval – and consists of two types of data: raw text (the description field) and knowledge graph or contextual elements (the other fields, such as title, tag, or category). Some of the contextual fields such as `agent` have been added post-crawling, using a clustering algorithm applied to the corpus. Then, `hash_ID[ID]` lists all the multitokens attached to text entity `ID`, with occurrence count for each. The full content attached to the ID is in `ID_to_content[ID]`, mapping IDs to text entities.

When processing a prompt, xLLM extracts all multitokens that are also present in the backend dictionary (itself built on the corpus), using a synonyms and acronyms table `KW_map` for exhaustivity. The goal is to match them to multitokens found in text entities. This step does not involve `embeddings`, which are used for a different purpose: finding related words.

The data gathered prior to returning the query results consists of entity IDs and their multitokens that match those from the prompt. Several metrics are linked to this data. In particular, whether a multitoken is in the contextual elements or in the regular text attached to a specific text entity, the length of the text entity and multitoken, the number of single tokens in the multitokens, the occurrence count attached to the multitoken across the whole corpus (stored in the multitoken `dictionary`), and whether a multitoken consists of adjacent tokens or not. From there, I build 4 scores to measure the fit between a text entity (represented by its ID), and the prompt:

- Score A: measuring the importance of the multitokens found both in the text entity, and in the prompt.
- Score B: number of multitokens found both in the text entity, and in the prompt (intersection).
- Score C: same as score A, but for multitokens also found in the contextual fields in the text entity.
- Score D: same as score B, but for multitokens also found in the contextual fields in the text entity.

These scores are computed in lines 326–341 in the code in section 10.4. In particular, the formula for Score A, for a specific text entity ID, is as follows:

$$\text{Score}_A[\text{ID}] = \sum_{t \in S_P[\text{ID}]} \lambda_t w_t^{-\beta_t}, \quad (10.1)$$

where $S_P[\text{ID}]$ is the set of multitokens found both in prompt P and in the text entity ID . Here $\lambda_t = 1$ and $\beta_t = 0.50$. Note the analogy with Formula (6.2) used in xLLM for predictions, also based on inverse powers. It favors rare tokens, which bear more weight in specialized search.

Traditional LLMs may use a negative value for β_t , and cosine metrics and/or parameters λ_t obtained via gradient descent, typically with neural networks. There is an implicit step activation function in Formula (10.1): the fact that tokens outside $S_P[\text{ID}]$ are ignored, further speeding up the computations. Such step functions are not recommended in neural networks, as it breaks the continuity and differentiability assumptions required for convergence of gradient descent. With xLLM, it is not an issue. Also neural networks are over-parameterized with millions of parameter sets producing the same output, to increase the odds of landing in a parameter configuration close to the optimum, during gradient descent. Again, xLLM does not face this problem.

One of the benefits is that no training is needed. It works with new tokens as the system is not pre-trained. Also, xLLM could be used as a starting point – a very good approximation close to the optimum – for LLMs relying on deep neural networks. Part of it is because xLLM bypasses all the continuity, linearity (tensors) and differentiability constraints attached to DNNs. But it remains to be seen whether DNNs can capitalize on this. In the case of tabular data synthetization, my NoGAN approach (see chapter 7) outperforms all DNNs both in terms of speed and quality, based on the best evaluation metrics.

I now describe how to build a `ranking system` for text entities, based on the four scores A, B, C, D. First, I sort the local `ID_hash` (a transposed of `hash_ID`) containing all the text entity IDs relevant to the prompt, in descending order, for each of the 4 scores. For each score, I only keep the ID ranks. See how `ID_hash` is built, in lines 315–324 in the code. Then I compute a global rank for each ID, using the function `rank_ID`. See line 345. The `rank_ID` function is listed in lines 214–239. In short, the global rank is a weighted combination of the 4 ranks originating from the 4 sorted scores: see line 236. The lower weights attached to scores B, C, D gives

them more importance over A, as they are related either to multitokens found in knowledge graph elements, or to multiple tokens consisting of several tokens.

10.2 Case study

Figures 10.1 and 10.2 show two prompts, and the text entity IDs retrieved by xLLM. To see the full content of these text entities, look at the anonymized input corpus `repository3.txt` on GitHub, [here](#). Each row is a text entity, starting with its ID. Note that IDs below 2000 (at the bottom of the file on GitHub) correspond to the original corpus, while IDs 2000 and higher comes from some augmentation.

```
-----
Prompt: List some data assets under the 'people' Business domain.
Cleaned: ['assets', 'business', 'data', 'domains', 'list', 'people']
-----
Most relevant text entities:

    ID wRank ID_Tokens
    24      7 {'business~domains': 1, 'business~domains~list': 1}
    433     10 {'domains~data': 1}
    151     10 {'business~data': 1}
    2701    12 {'people': 1, '__people': 1}
    42      12 {'data~assets': 1}
    48      12 {'data~assets': 1}
    90      12 {'data~assets': 1}
    91      12 {'data~assets': 1}
    92      12 {'data~assets': 1}
    199     12 {'data~assets': 1}
```

Figure 10.1: Text entities retrieved by xLLM and associated multitokens, first example

```
-----
Prompt: Identify the parent DLZ of the geographical zone AFR in the MLTxQuest hierarchy.
Cleaned: ['afr', 'dlz', 'geographical', 'hierarchy', 'identify', 'mltxquest', 'zone']
-----
Most relevant text entities:

    ID wRank ID_Tokens
    2919     9 {'zone': 1, 'hierarchy': 1}
    433      9 {'zone': 1, 'hierarchy': 1}
    2012    10 {'zone': 1, 'mltxquest': 1, 'afr': 1}
    2655    14 {'hierarchy': 1}
    2075    14 {'geographical': 1}
    2479    14 {'geographical': 1}
    2844    14 {'geographical': 1}
    3252    15 {'mltxquest': 1, 'afr': 1}
    2154    16 {'zone': 1, 'mltxquest': 1, 'dlz': 1}
    2220    19 {'zone': 1, 'dlz': 1}
```

Figure 10.2: Text entities retrieved by xLLM and associated multitokens, second example

Multitoken counters are all equal to 1 here because the text entities are short and do not contain a same multitoken more than once. The order in which IDs are shown depends heavily on β (see `beta=0.50` in line 249 in the code) and the weight vector [2, 1, 1, 1] attached to the 4 scores A, B, C, D, initialized in line 236 in the code. It also depends on the size and number of text entities, that is, on the `chunking` mechanism. Significant improvement can be achieved by adding entries to `KW_map`, for instance ‘pple’ pointing to ‘people’, and ‘PeopleDomain’ pointing to ‘people domain’. Or via additional NLP when parsing the corpus.

The 10 text entity IDs shown in Figures 10.1 and 10.2 are only a small subset of what xLLM found, selected via the ranking mechanism. Also note the token starting with ‘__’ in Figure 10.1, identifying a `graph token`. It comes from a knowledge graph element in text entity 2701, rather than from regular text.

10.2.1 xLLM for auto-indexing and glossary generation

In the end, one has to question the need for billions of tokens and weights, when less than a few thousands cover more than what could come from prompts. The total number of meaningful prompts of any length, after cleaning, is probably well below a million for this sub-LLM. This includes all past and future prompts. One

might generate all of them with a **prompt synthesizer** and then create the answer for each of them, resulting in Q&A list with a million entries, easily manageable.

Besides search and retrieval, another possible application of xLLM is to automatically update the corpus by adding relevant material in text entities, based on augmentation, or detecting and deduping redundant entries. Or to build a taxonomy on the corpus, possibly seeded using some external taxonomy, via **taxonomy augmentation**. You can also use xLLM as an **auto-indexer** and **glossary generation** for books, large websites or repositories: it will automatically detect index entries and sub-entries, create the full index or glossary, and flag the corresponding terms in the corpus using a mechanism similar to text entity IDs. At the time of writing, the only product offering this capability is **notebookML**.

Another topic of interest is to study the patterns found in the corpus, versus those found in prompts, to eventually increase the compatibility between what the user is looking for, and what is available in the corpus. Stopwords lists attached to prompts may be different from those attached to the corpus.

Finally, xLLM can be used along with other LLMs to re-inforce or judge each other. Large companies do not stick to just one product. They like to have more than just one tool. One of the challenge is automated **model evaluation**: xLLM returns concise yet exhaustive bullet lists with a score attached to each item, see Figure 10.4. How do you assess exhaustivity? How to take into accounts the relevancy scores in your evaluation metric? In chapter 5, I discuss an approach based on the ability to correctly reconstruct the underlying taxonomy in the corpus. Another idea is to use xLLM to generate an index, and compare it with the existing one in the corpus.

10.3 xLLM for scientific research

The first version of xLLM was not intended for corporate clients, but for scientific research. The goal was to find references, links, and related topics to specific research questions or keywords. Yet it is based on the same architecture, refined over time with the introduction of **nested hashes** as the core database structure. See section 7.2 in [13] for a detailed description, including smart crawling to retrieve the taxonomy embedded in the corpus. In this example, the Wolfram website and its large, high-quality taxonomy.

```
ORGANIC URLs
5 https://mathworld.wolfram.com/CentralLimitTheorem.html
3 https://mathworld.wolfram.com/LyapunovCondition.html
2 https://mathworld.wolfram.com/NormalDistribution.html
2 https://mathworld.wolfram.com/Feller-LevyCondition.html
2 https://mathworld.wolfram.com/LindebergCondition.html
2 https://mathworld.wolfram.com/Lindeberg-FellerCentralLimitTheorem.html
1 https://mathworld.wolfram.com/Berry-EsseenTheorem.html
1 https://mathworld.wolfram.com/ExtremeValueDistribution.html
1 https://mathworld.wolfram.com/WeakLawofLargeNumbers.html

CATEGORIES & LEVELS
5 Central Limit Theorem | Limit Theorems | 4
3 Lyapunov Condition | Limit Theorems | 4
2 Normal Distribution | Continuous Distributions | 4
2 Feller-Levy Condition | Limit Theorems | 4
2 Lindeberg Condition | Limit Theorems | 4
2 Lindeberg-Feller Central Limit Theorem | Limit Theorems | 4
1 Berry-Esseen Theorem | Moments | 3
1 Extreme Value Distribution | Continuous Distributions | 4
1 Weak Law of Large Numbers | Limit Theorems | 4

RELATED
13 Central Limit Theorem
9 Berry-Esseen Theorem
7 Lindeberg Condition
5 Fourier Transform--Gaussian
5 Lindeberg-Feller Central Limit Theorem
5 Lyapunov Condition
4 Normal Distribution Function
4 Feller-Levy Condition
2 Binomial Distribution
2 Bivariate Normal Distribution
```

Figure 10.3: xLLM for scientific research, looking for ‘central limit theorem’

It turns out that many websites including Wikipedia or Amazon, as well as corporate corpuses, have a

very similar structure. It makes it easy to adapt the system to a variety of environments. The reason to include xLLM for research in this section, is to show how it performs compared to others. If you look at Figure 10.3 and 10.4, it is obvious that xLLM serves professional users a lot better than OpenAI. Other comparisons with Google search, Gemini, Bing AI, and even the internal Wolfram search box, lead to the same conclusion: they all favor rudimentary results, with long English sentences that take time to read, returning information that you already know. By contrast, xLLM returns concise but exhaustive bullet lists grouped by section, with a relevancy score attached to each item, and deep rather than shallow content.

The Python code, input data (full crawled Wolfram corpus covering mathematics and computer science), as well as backend tables, are available on GitHub, [here](#). The sub-folder `enterprise` deals with the enterprise version discussed in sections 10.1 and 10.2.

The screenshot shows a ChatGPT interface. At the top left is a green circular icon with a white 'G'. To its right is the text "ChatGPT". Below this is a text box containing the following content:

The Central Limit Theorem (CLT) is a fundamental concept in probability theory and statistics. It states that, under certain conditions, the distribution of the sum (or average) of a large number of independent, identically distributed random variables will be approximately normally distributed, regardless of the original distribution of the individual variables.

Here are the key points of the Central Limit Theorem:

1. **Independence:** The random variables should be independent of each other. This means that the occurrence of one event does not affect the occurrence of another.
2. **Identically Distributed:** The random variables should be drawn from the same probability distribution. This ensures that they have the same mean and standard deviation.
3. **Large Sample Size:** The theorem is most effective for large sample sizes. As a general rule of thumb, a sample size of 30 or more is often considered large enough for the CLT to apply, although this can vary depending on the underlying distribution.

The Central Limit Theorem has significant implications for statistical inference. Even if the original population distribution is not normal, the distribution of sample means from that population will tend to be normal for sufficiently large sample sizes. This normal distribution is often used to make inferences about population parameters using methods such as hypothesis testing and confidence intervals.

In practical terms, the Central Limit Theorem is frequently employed when working with sample means, as it allows statisticians to make assumptions about the distribution of sample means even when the original population distribution is unknown or not normally distributed.

Figure 10.4: Looking for ‘central limit theorem’, using OpenAI GPT

10.4 Python code

The Python code here pertains to the enterprise version v2 of xLLM, discussed in sections 10.1 and 10.2. It is on GitHub, in my Large-Language-Models/xllm6/enterprise/ sub-folder, [here](#). Look for

- `xllm-enterprise-v2-dev.py`, the main program listed here,
- `xllm_enterprise_util.py`, the accompanying library,
- `repository3.txt`, the anonymized augmented corpus used as input source,
- `enterprise_sample_prompts.txt`, a list of sample prompts,
- `xllm-enterprise-v2-dev-output.txt`, the output results for all sample prompts.

```

1 import xllm_enterprise_util as exllm
2
3 #--- Backend: create backend tables based on crawled corpus
4
5 tableNames = (
6     'dictionary', # multitokens (key = multitoken)

```

```

7   'hash_pairs', # multitoken associations (key = pairs of multitokens)
8   'ctokens', # not adjacent pairs in hash_pairs (key = pairs of multitokens)
9   'hash_context1', # categories (key = multitoken)
10  'hash_context2', # tags (key = multitoken)
11  'hash_context3', # titles (key = multitoken)
12  'hash_context4', # descriptions (key = multitoken)
13  'hash_context5', # meta (key = multitoken)
14  'hash_ID', # text entity ID table (key = multitoken, value is list of IDs)
15  'hash_agents', # agents (key = multitoken)
16  'full_content', # full content (key = multitoken)
17  'ID_to_content', # full content attached to text entity ID (key = text entity ID)
18  'ID_to_agents', # map text entity ID to agents list (key = text entity ID)
19  'ID_size', # content size (key = text entity ID)
20  'KW_map', # for singularization, map kw to single-token dictionary entry
21  'stopwords', # stopword list
22 )
23
24 backendTables = {}
25 for name in tableNames:
26     backendTables[name] = {}
27
28 stopwords = ('', '-', 'in', 'the', 'and', 'to', 'of', 'a', 'this', 'for', 'is', 'with', 'from',
29             'as', 'on', 'an', 'that', 'it', 'are', 'within', 'will', 'by', 'or', 'its', 'can',
30             'your', 'be', 'about', 'used', 'our', 'their', 'you', 'into', 'using', 'these',
31             'which', 'we', 'how', 'see', 'below', 'all', 'use', 'across', 'provide', 'provides',
32             'aims', 'one', '&', 'ensuring', 'crucial', 'at', 'various', 'through', 'find', 'ensure',
33             'more', 'another', 'but', 'should', 'considered', 'provided', 'must', 'whether',
34             'located', 'where', 'begins', 'any', 'what', 'some', 'under', 'does', 'belong',
35             'included', 'part', 'associated')
36 backendTables['stopwords'] = stopwords
37
38 # agent_map works, but hash structure should be improved
39 # key is word, value is agent (many-to-one). Allow for many-to-many
40 agent_map = {
41     'template':'Template',
42     'policy':'Policy',
43     'governance':'Governance',
44     'documentation':'Documentation',
45     'best practice':'Best Practices',
46     'bestpractice':'Best Practices',
47     'standard':'Standards',
48     'naming':'Naming',
49     'glossary':'Glossary',
50     'historical data':'Data',
51     'overview':'Overview',
52     'training':'Training',
53     'genai':'GenAI',
54     'gen ai':'GenAI',
55     'example':'Example',
56     'example1':'Example',
57     'example2':'Example',
58 }
59
60 KW_map = {}
61 save_KW_map = False
62 try:
63     IN = open("KW_map.txt","r")
64 except:
65     print("KW_map.txt not found on first run: working with empty KW_map.")
66     print("KW_map.txt will be created after exiting if save = True.")
67     save_KW_map = True
68 else:
69     # plural in dictionary replaced by singular form
70     content = IN.read()
71     pairs = content.split('\n')
72     for pair in pairs:
73         pair = pair.split('\t')
74         key = pair[0]
75         if len(pair) > 1:
76             KW_map[key] = pair[1]
77     IN.close()
78
79 # manual additions (plural not in prompt but not dictionary, etc.)
80 KW_map['domains'] = 'domain'
81 KW_map['doing business as'] = 'dba'
82

```

```

83 backendTables['KW_map'] = KW_map
84
85 backendParams = {
86     'max_multitoken': 4, # max. consecutive terms per multi-token for inclusion in dictionary
87     'maxDist' : 3, # max. position delta between 2 multitokens to link them in hash_pairs
88     'maxTerms' : 3, # maxTerms must be <= max_multitoken
89     'extraWeights' : # deafault weight is 1
90     {
91         'description': 0.0,
92         'category': 0.3,
93         'tag_list': 0.4,
94         'title': 0.2,
95         'meta': 0.1
96     }
97 }
98
99
100 #--- Read repository and create all backend tables
101
102 # https://raw.githubusercontent.com/VincentGranville
103 #   /Large-Language-Models/refs/heads/main/xllm6/enterprise/repository3.txt
104
105 IN = open("repository3.txt", "r")
106 data = IN.read()
107 IN.close()
108
109 entities = data.split("\n")
110 ID_size = backendTables['ID_size']
111
112 # to avoid duplicate entities (takes space, better to remove them in the corpus)
113 entity_list = ()
114
115 for entity_raw in entities:
116
117     entity = entity_raw.split("~~")
118     agent_list = ()
119
120     if len(entity) > 1 and entity[1] not in entity_list:
121
122         entity_list = (*entity_list, entity[1])
123         entity_ID = int(entity[0])
124         entity = entity[1].split("{")
125         hash_crawl = {}
126         hash_crawl['ID'] = entity_ID
127         ID_size[entity_ID] = len(entity[1])
128         hash_crawl['full_content'] = entity_raw # do not build to save space
129
130         key_value_pairs = exllm.get_key_value_pairs(entity)
131
132         for pair in key_value_pairs:
133
134             if ":" in pair:
135                 key, value = pair.split(": ", 1)
136                 key = key.replace("//", "")
137                 if key == 'category_text':
138                     hash_crawl['category'] = value
139                 elif key == 'tags_list_text':
140                     hash_crawl['tag_list'] = exllm.clean_list(value)
141                 elif key == 'title_text':
142                     hash_crawl['title'] = value
143                 elif key == 'description_text':
144                     hash_crawl['description'] = value # do not build to save space
145                 elif key == 'tower_option_tower':
146                     hash_crawl['meta'] = value
147                 if key in ('category_text', 'tags_list_text', 'title_text'):
148                     for word in agent_map:
149                         if word in value.lower():
150                             agent = agent_map[word]
151                             if agent not in agent_list:
152                                 agent_list = (*agent_list, agent)
153
154             hash_crawl['agents'] = agent_list
155             exllm.update_dict(backendTables, hash_crawl, backendParams)
156
157
158 #--- Create embeddings

```

```

159 embeddings = {} # multitoken embeddings based on hash_pairs
160
161 hash_pairs = backendTables['hash_pairs']
162 dictionary = backendTables['dictionary']
163
164 for key in hash_pairs:
165     wordA = key[0]
166     wordB = key[1]
167     nA = dictionary[wordA]
168     nB = dictionary[wordB]
169     nAB = hash_pairs[key]
170     pmi = nAB/(nA*nB)**0.5 # try: nAB/(nA + nB - nAB)
171     # if nA + nB <= nAB:
172     #     print(key, nA, nB, nAB)
173     exllm.update_nestedHash(embeddings, wordA, wordB, pmi)
174     exllm.update_nestedHash(embeddings, wordB, wordA, pmi)
175
176
177 #--- Create sorted n-grams
178
179 sorted_ngrams = {} # to match ngram prompts with embeddings entries
180
181 for word in dictionary:
182     tokens = word.split('`')
183     tokens.sort()
184     sorted_ngram = tokens[0]
185     for token in tokens[1:len(tokens)]:
186         sorted_ngram += "`" + token
187     exllm.update_nestedHash(sorted_ngrams, sorted_ngram, word)
188
189 # print top multitokens: useful to build agents, along with sample prompts
190 # for key in dictionary:
191 #     if dictionary[key] > 20:
192 #         print(key, dictionary[key])
193
194
195 #--- Functions used to score results ---
196
197 def rank(hash):
198     # sort hash, then replace values with their rank
199
200     hash = dict(sorted(hash.items(), key=lambda item: item[1], reverse=True))
201     rank = 0
202     old_value = 999999999999
203
204     for key in hash:
205         value = hash[key]
206         if value < old_value:
207             rank += 1
208         hash[key] = rank
209         old_value = value
210     return(hash)
211
212
213 def rank_ID(ID_score):
214     # attach weighted relevancy rank to text entity ID, with respect to prompt
215
216     ID_score0 = {}
217     ID_score1 = {}
218     ID_score2 = {}
219     ID_score3 = {}
220
221     for ID in ID_score:
222         score = ID_score[ID]
223         ID_score0[ID] = score[0]
224         ID_score1[ID] = score[1]
225         ID_score2[ID] = score[2]
226         ID_score3[ID] = score[3]
227
228     ID_score0 = rank(ID_score0)
229     ID_score1 = rank(ID_score1)
230     ID_score2 = rank(ID_score2)
231     ID_score3 = rank(ID_score3)
232
233     ID_score_ranked = {}

```



```

311     # --- Scoring and selecting what to show in prompt results ---
312
313     exllm.distill_frontendTables(q_dictionary, q_embeddings, frontendParams)
314     hash_ID = backendTables['hash_ID']
315     ID_hash = {} # local, transposed of hash_ID; key = ID; value = multitoken list
316
317     for word in q_dictionary:
318         for ID in hash_ID[word]:
319             exllm.update_nestedHash(ID_hash, ID, word, 1)
320             gword = "__" + word # graph multitoken
321             if gword in hash_ID:
322                 for ID in hash_ID[gword]:
323                     exllm.update_nestedHash(ID_hash, ID, gword, 1)
324
325     ID_score = {}
326     for ID in ID_hash:
327         # score[0] is inverse weighted count
328         # score[1] is raw number of tokens found
329         score = [0, 0] # based on tokens present in the entire text entity
330         gscore = [0, 0] # based on tokens present in graph
331         for token in ID_hash[ID]:
332             if token in dictionary:
333                 score[0] += 1/(q_dictionary[token]**beta)
334                 score[1] += 1
335             else:
336                 # token must start with "__" (it's a graph token)
337                 token = token[2:len(token)]
338                 gscore[0] += 1/(q_dictionary[token]**beta)
339                 gscore[1] += 1
340         ID_score[ID] = [score[0], score[1], gscore[0], gscore[1]]
341
342     # --- Print results ---
343
344     ID_score_ranked = rank_ID(ID_score)
345     n_ID = 0
346     print("Most relevant text entities:\n")
347     print("\n  ID wRank ID_Tokens")
348     for ID in ID_score_ranked:
349         if n_ID < 10:
350             # content of text entity ID not shown, stored in ID_to_content[ID]
351             print(" %5d %3d %s" %(ID, ID_score_ranked[ID], ID_hash[ID]))
352             n_ID += 1
353
354     print("\nToken count (via dictionary):\n")
355     for key in q_dictionary:
356         print(" %4d %s" %(q_dictionary[key], key))
357
358     q_embeddings = dict(sorted(q_embeddings.items(), key=lambda item: item[1], reverse=True))
359     n_words = 0
360     print("\nTop related tokens (via embeddings):\n")
361     for word in q_embeddings:
362         pmi = q_embeddings[word]
363         if n_words < 10:
364             print(" %5.2f %s" %(pmi, word))
365             n_words += 1
366
367
368     #--- Save backend tables
369
370     def create_KW_map(dictionary):
371         # singularization
372         # map key to KW_map[key], here key is a single token
373         # need to map unseen prompt tokens to related dictionary entries
374         # example: ANOVA -> analysis~variance, ...
375
376         OUT = open("KW_map.txt", "w")
377         for key in dictionary:
378             if key.count('~') == 0:
379                 j = len(key)
380                 keyB = key[0:j-1]
381                 if keyB in dictionary and key[j-1] == 's':
382                     if dictionary[key] > dictionary[keyB]:
383                         OUT.write(keyB + "\t" + key + "\n")
384                     else:
385                         OUT.write(key + "\t" + keyB + "\n")
386

```

```
387     OUT.close()
388     return()
389
390 if save_KW_map:
391     # save it only if it does not exist
392     create_KW_map(dictionary)
393
394 save = True
395 if save:
396     for tableName in backendTables:
397         table = backendTables[tableName]
398         OUT = open('backend_' + tableName + '.txt', "w")
399         OUT.write(str(table))
400         OUT.close()
401
402 OUT = open('backend_embeddings.txt', "w")
403 OUT.write(str(embeddings))
404 OUT.close()
405
406 OUT = open('backend_sorted_ngrams.txt', "w")
407 OUT.write(str(sorted_ngrams))
408 OUT.close()
```

Bibliography

- [1] Fabiola Banfi, Greta Cazzaniga, and Carlo De Michele. Nonparametric extrapolation of extreme quantiles: a comparison study. *Stochastic Environmental Research and Risk Assessment*, 36:1579–1596, 2022. [\[Link\]](#). 94, 161
- [2] Marc G. Bellemare et al. The Cramer distance as a solution to biased Wasserstein gradients. *Preprint*, pages 1–20, 2017. arXiv:1705.10743 [\[Link\]](#). 98
- [3] Iulia Brezeanu. How to cut RAG costs by 80% using prompt compression. *Blog post*, 2024. TowardsData-Science [\[Link\]](#). 31, 137
- [4] Wei Chen and Mark Fuge. Synthesizing designs with interpart dependencies using hierarchical generative adversarial networks. *Journal of Mechanical Design*, 141:1–11, 2019. [\[Link\]](#). 93
- [5] Johnathan Chiu, Andi Gu, and Matt Zhou. Variable length embeddings. *Preprint*, pages 1–12, 2023. arXiv:2305.09967 [\[Link\]](#). 31, 136
- [6] Fabian Gloeckle et al. Better & faster large language models via multi-token prediction. *Preprint*, pages 1–29, 2024. arXiv:2404.19737 [\[Link\]](#). 31, 67
- [7] Vincent Granville. Generative AI: Synthetic data vendor comparison and benchmarking best practices. *Preprint*, pages 1–13, 2023. MLTechniques.com [\[Link\]](#). 90, 98
- [8] Vincent Granville. Generative AI technology break-through: Spectacular performance of new synthesizer. *Preprint*, pages 1–16, 2023. MLTechniques.com [\[Link\]](#). 80, 83
- [9] Vincent Granville. *Gentle Introduction To Chaotic Dynamical Systems*. MLTechniques.com, 2023. [\[Link\]](#). 144, 146, 147, 150
- [10] Vincent Granville. How to fix a failing generative adversarial network. *Preprint*, pages 1–10, 2023. MLTechniques.com [\[Link\]](#). 82
- [11] Vincent Granville. Massively speed-up your learning algorithm, with stochastic thinning. *Preprint*, pages 1–13, 2023. MLTechniques.com [\[Link\]](#). 81
- [12] Vincent Granville. Smart grid search for faster hyperparameter tuning. *Preprint*, pages 1–8, 2023. MLTechniques.com [\[Link\]](#). 47, 81, 115
- [13] Vincent Granville. *State of the Art in GenAI & LLMs – Creative Projects, with Solutions*. MLTechniques.com, 2024. [\[Link\]](#). 126, 166, 168
- [14] Vincent Granville. *Statistical Optimization for AI and Machine Learning*. MLTechniques.com, 2024. [\[Link\]](#). 54, 112, 114, 115, 135, 137, 166
- [15] Vincent Granville. *Synthetic Data and Generative AI*. Elsevier, 2024. [\[Link\]](#). 135, 168
- [16] Vincent Granville, Mirko Krivanek, and Jean-Paul Rasson. Simulated annealing: A proof of convergence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 16:652–656, 1996. 100
- [17] Albert Jiang et al. Mixtral of experts. *Preprint*, pages 1–13, 2024. arXiv:2401.04088 [\[Link\]](#). 31
- [18] L. Kuipers and H. Niederreiter. *Uniform Distribution of Sequences*. Dover, 2012. [\[Link\]](#). 149
- [19] Jogendra Nath Kundu et al. GAN-Tree: An incrementally learned hierarchical generative framework for multi-modal data distributions. *IEEE/CVF International Conference on Computer Vision*, pages 8190–8199, 2019. arXiv:1908.03919 [\[Link\]](#). 93
- [20] Nicolas Langrené and Xavier Warin. Fast multivariate empirical cumulative distribution function with connection to kernel density estimation. *Computational Statistics & Data Analysis*, 162:1–16, 2021. [\[Link\]](#). 99
- [21] Tengyuan Liang. Estimating certain integral probability metric (IPM) is as hard as estimating under the IPM. *Preprint*, pages 1–15, 2019. arXiv:1911.00730 [\[Link\]](#). 99
- [22] Andrei Lopatenko. Evaluating LLMs and LLM systems: Pragmatic approach. *Blog post*, 2024. [\[Link\]](#). 31

- [23] Sebastián Maldonado et al. An adaptive loss function for deep learning using OWA operators. *Preprint*, pages 1–15, 2023. arXiv:2305.19443 [Link]. 111
- [24] Hussein Mozannar et al. The RealHumanEval: Evaluating Large Language Models’ abilities to support programmers. *Preprint*, pages 1–34, 2024. arXiv:2404.02806 [Link]. 31
- [25] Michael Naaman. On the tight constant in the multivariate Dvoretzky–Kiefer–Wolfowitz inequality. *Statistics & Probability Letters*, 173:1–8, 2021. [Link]. 99
- [26] Sergey Shchegrikovich. How do you create your own LLM and win The Open LLM Leaderboard with one Yaml file? *Blog post*, 2024. [Link]. 31
- [27] Bharath Sriperumbudur et al. On the empirical estimation of integral probability metrics. *Electronic Journal of Statistics*, pages 1550–1599, 2012. [Link]. 99
- [28] Chang Su, Linglin Wei, and Xianzhong Xie. Churn prediction in telecommunications industry based on conditional Wasserstein GAN. *IEEE International Conference on High Performance Computing, Data, and Analytics*, pages 186–191, 2022. IEEE HiPC 2022 [Link]. 93
- [29] Eyal Trabelsi. Comprehensive guide to approximate nearest neighbors algorithms. *Blog post*, 2020. TowardsDataScience [Link]. 138
- [30] Jinsung Yoon et al. GAIN: Missing data imputation using generative adversarial nets. *Preprint*, pages 1–10, 2018. arXiv:1806.02920 [Link]. 93

Index

- χ^2 distribution, 150
- k -NN, 52, 135
- k -means clustering, 68
- k -medoids clustering, 68
- n -gram, 8
 - sorted, 50
- p -adic valuation, 145
- p -value, 150, 152
- abbreviation dictionary, 14
- acronym, 52
- acronyms, 46
- action, 8, 12, 51
- activation function, 100
- Adam (stochastic gradient descent), 52
- agent, 12, 18, 29, 46, 53, 123
 - multi-agent, 51
- ANN (approximate nearest neighbors search), 44, 54
 - probabilistic ANN (pANN), 52
- ANN (approximate nearest neighbors), 137
 - probabilistic ANN (pANN), 137
- approximated nearest neighbors, 135
- augmentation, 15, 48, 52
 - augmented knowledge graph, 15
 - taxonomy augmentation, 15, 126
- auto-correct, 14
- auto-encoder, 52
- auto-regressive model, 53
- auto-tuning, 92, 98, 100
- backend, 29, 52, 53, 123
- base, 149
- batch, 92, 94, 100
- Bayesian hierarchical models, 93
- benchmarking, 52
- Beurling primes, 168
- binary search
 - interpolated, 138
- binning, 112
- bit shift, 148
- bootstrapping, 70
- caching, 44, 54
- categorical feature, 92
- central limit theorem, 166
- confidence interval, 166
- confidence intervals, 70
 - model-free, 83
- congruential equidistribution
 - asymptotic, 148
- connected components, 68
- context, 123
 - contextual pairs, 45
 - contextual tables, 45
 - contextual tokens, 45
- convolution product, 159
- copula, 93, 101
- cosine similarity, 54, 137
- covariance matrix, 114
- Cramér's V, 92
- crawling
 - smart crawling, 8, 45
- cross-validation, 48, 69, 90
- customization (LLM), 49
- data distillation, 81
- database
 - graph database, 53
 - JSON, 48
 - key-value pairs, 48
 - nested hash, 48
 - vector database, 48
- debugging, 49
- deep neural network, 100
- deep neural network (DNN), 52, 111
- dendrogram, 70
- diffusion, 52, 82
- diffusion model, 159
- digit block, 146
- digit-preserving, 146
- Dirichlet character, 168
- Dirichlet- L function, 168
- distance matrix, 67
- distillation, 14, 46, 52
- distributed computing, 46
- DNN (deep neural network), 45
- dot product, 136
- dummy variable, 92
- ECDF (empirical distribution), 54, 80, 111
- ECDF empirical distribution, 91
- embedding, 19, 45, 52
 - quantized embedding, 48
 - variable length embedding, 7, 48
- embeddings
 - variable length, 136
- empirical density function, 99
- empirical distribution, 68
 - multivariate, 54, 80, 90, 93, 99, 111, 138
- encoding
 - smart encoding, 69
- EPDF (empirical probability density function), 111

- epoch (neural networks), 135, 139
- equidistribution modulo 1, 149
- Euler product, 168
- evaluation (GenAI models), 111
- evaluation metric, 52
- evaluation metrics, 48, 53
- exhaustivity (LLM/RAG output), 123
- explainable AI, 50, 52, 80, 90, 100
- feature encoding, 54
- feature engineering, 53
- fine-tuning, 52
 - exhaustive results, 47, 123
 - in real time, 17
 - LLM parameters, 46
 - self-tuning, 49
- frontend, 52
- GAN (generative adversarial network), 13, 80, 111, 159
 - hierarchical GAN, 93
 - NoGAN, 14
- Gaussian mixture model, 114, 159
- generative adversarial network, 52, 82, 90, 137, 159
- GPT, 52
- GPU, 47
- gradient descent, 70, 91, 100, 114, 135
 - steepest, 139
 - stochastic, 111, 139
- graph
 - graph database, 53
 - knowledge graph, 48
- GRH (Generalized Riemann Hypothesis), 168
- grid search, 81
 - smart grid search, 47, 115
- Hadamard product, 91
- hallucination, 48
- hash table
 - inversion, 67
 - nested hash, 8, 45, 46, 48, 53, 67, 123, 126
- Hellinger distance, 99, 111
 - multivariate, 45
- hierarchical Bayesian model, 101
- hierarchical clustering, 68
- hierarchical deep resampling, 90, 93
- holdout, 93
- Hungarian algorithm, 111, 135
- hyperparameter, 47, 50, 52, 81, 92
- hyperrectangles, 80
- identifiability (statistics), 134
- imputation (missing values), 93
- in-memory database, 16
- in-memory LLM, 16, 47
- indexing
 - auto-indexing, 126
 - glossary generation, 126
 - text entity index, 48, 123
- integer division, 148
- integral probability metrics, 99
- JSON, 8, 45
- database, 48, 53
- kernel, 159
- kernel density estimation, 159
- key-value database, 8, 53
- knowledge graph, 123
- knowledge graph, 48
- Kolmogorov-Smirnov distance, 68, 80, 92, 93, 99, 113, 138
- multivariate, 45, 54, 111
- label feature, 98
- LangChain, 53
- large language model
 - evaluation, 126
- large language models (LLM), 57
- latency, 15
- law of the iterated logarithm, 150
- LLaMA, 45, 53
- LLM (large language model)
 - agentic LLM, 12
 - debugging, 49
 - for auto-indexing, 126
 - for clustering, 13
 - for glossary generation, 126
 - for predictive analytics, 13
 - in-memory, 16
 - LLM router, 8, 46, 123
 - multi-LLM, 17
 - self-tuned, 49
 - sub-LLM, 17, 123
 - xLLM, 17
- loss function, 68, 70, 91, 92, 100, 111, 135, 139
 - adaptive loss, 45, 111
- matrix
 - positive semidefinite, 114
- Mersenne twister, 144, 147
- mixture model, 99
- mixture of experts, 46, 49, 123
- multi-agent system, 51, 53
- multimodal system, 53
- multinomial distribution, 80
- multitoken (see token), 52
- nearest neighbors
 - K-NN, 134
 - approximate (ANN), 134
 - probabilistic (pANN), 134
- NLG (natural language generation), 53
- NLP (natural language processing), 14, 53
- node (interpolation), 99
- NoGAN, 52, 80, 112, 137
 - constrained, 112
 - probabilistic, 112
- normal number, 149
- normalization, 53, 54
- notebookML, 126
- OpenAI, 114
- overfitting, 47, 68, 80

parameter
in neural networks, 53, 54
in xLLM, 53
period, 145
PMI (pointwise mutual information), 7, 9, 19, 31, 49, 50
pointwise mutual information (PMI), 54, 136
Poisson process, 139
positive semidefinite (matrix), 114
prefix, 145
principal component analysis, 93
PRNG (pseudo-random number generator), 14, 47, 144
probability density function, 159
prompt
command prompt options, 48
prompt engineering, 48
synthesizer, 126
prompt compression, 137
Python library
GenAI-evaluation, 113
Sklearn, 68
Sklearn_extra, 68
quantile, 81, 113
extrapolated, 161
quantile function, 94, 159
quantization, 48
Rademacher function, 168
radix search, 138
RAG (retrieval augmentation generation), 15, 53, 123
random walk
simple, 150
rank
relevancy rank, 124
regularization, 54
reinforcement learning, 49, 54, 100
rejection sampling, 161
relevancy
relevancy score, 47, 50, 123
replicability, 47
reproducibility, 14, 47
resampling, 112
residue, 148
retrieval, 48
retrieval augmentation generation (RAG), 53
Riemann hypothesis
generalized, 168
Riemann zeta function, 168
run test, 148
scalability, 15
score
relevancy rank, 124
relevancy score, 29, 47
search
probabilistic search, 48
vector search, 48
seed (random number generator), 13, 92
self-tuning, 52, 54
separator (text), 54
similarity metric, 68
simulated annealing, 100
singularization, 14
stemming, 14
stopwords, 8, 49
swap, 91, 100
synonyms dictionary, 14
synthetic data, 54, 111, 161
constrained, 112, 115
synthetic function, 168
taxicab distance, 139
taxonomy, 53
augmentation, 126
taxonomy creation, 57, 126
tensor, 92
TensorFlow, 92
text entity, 12, 29, 46, 48, 52, 123
sub-entity, 18
text entity ID, 29
time complexity, 81
token, 52, 54
contextual, 45, 67
graph token, 123, 125
multi-token, 67
multitoken, 7, 19, 52, 123
training, 47, 52
transformer, 13, 45, 47, 52, 54, 100
truncated Gaussian, 161
unit ball, 139
validation set, 80, 93
vanishing gradient, 92
variational auto-encoder, 52
vector database, 48, 54
vector search, 48, 54, 134
vectorization, 81
Wasserstein GAN, 100
Wasserstein GAN (WGAN), 111
Weibull distribution, 139
Wiener process, 150
XGboost, 80
xLLM, 17, 57
e-xLLM (for enterprise corpus), 123