Understanding AI Data Repositories with Automatic Query Generation

Erik Altman

Abstract

We describe a set of techniques to generate queries automatically based on one or more ingested, input corpuses. These queries require no a priori domain knowledge, and hence no human domain experts. Thus, these auto-generated queries help address the epistemological question of how we know what we know, or more precisely in this case, how an AI system with ingested data knows what it knows.

These auto-generated queries can also be used to identify and remedy problem areas in ingested material – areas for which the knowledge of the AI system is incomplete or even erroneous. Similarly, the proposed techniques facilitate tests of AI capability – both in terms of coverage and accuracy.

By removing humans from the main learning loop, our approach also allows more effective scaling of AI and cognitive capabilities to provide (1) broader coverage in a single domain such as health or geology; and (2) more rapid deployment to new domains. The proposed techniques also allow ingested knowledge to be extended naturally.

Our investigations are early, and this paper provides a description of the techniques. Assessment of their efficacy is our next step for future work.

1 Introduction

Broadly speaking, AI or cognitive solutions must follow the “URL” principles: Understand, Reason, Learn. A core challenge for all three of these URL aspects is ingesting input material on specific topics, and then making broad, reliable, and useful inferences based on that material. Put simply, training is hard. Machine learning, deep learning, and DeepQA [1] offer techniques to provide URL. However, when they are applied to new domains and new corpuses of information, extensive human intervention is often required to ensure that the ingested information is being properly understood, and that reasoning and learning about it is producing reasonable conclusions.

This human intervention is required in significant measure because the ingestion process does not have a natural way to assess its efficacy, and take corrective action when efficacy is found wanting. Put another way, human intervention is required to address the problem of unknowns: AI ingestion systems do not know what they have not learned.

To address this problem of unknowns, it would help to have an automated means to generate an interesting and broad set of queries on ingested content, and that is what we
propose here. To the degree that we can provide good answers to such automatically generated queries, we know that the ingestion has worked well. Further, to the degree we do not provide good answers, the generated queries provide specific actionable gaps to address. In turn, the gaps exposed by specific generated queries may be addressed – at least in part – by looking to other corpuses of data. In looking at those other corpuses, we can of course leverage the standard techniques of machine learning, deep learning, DeepQA, etc. to find the queried information.

This ingest-query combination in turn enables a virtuous cycle: automated knowledge extraction – query generation – automated knowledge extraction – etc., where each step checks and expands upon the previous step. For example, adding information from additional sources may yield additional learning based on the cross-product of the original and newly added material. In some sense this process mirrors the human research endeavor: understand material, look elsewhere when key questions are not answered, then pursue new questions revealed by additional knowledge.

More specifically, this approach leverages three elements: (1) the automatic query generation proposed here; (2) DeepQA, machine learning, and deep learning for resolving the generated queries; and (3) checks on the utility of the responses from (2). These three elements in combination provide an automated means (a) to check if a corpus has been effectively ingested and understood; (b) to check if the ingested corpus provides broad coverage of the desired domain; (c) to extend the knowledge in the ingested domain corpus to cover a broader set of knowledge; and (d) to iterate across (a) - (c) to continually improve capabilities and accuracy. In combination, capabilities (a) - (d) provide an opportunity to automate and scale our cognitive capabilities.

The remainder of this paper outlines a number of ideas on how to address this missing link of automatic query generation for ingested corpuses of data. However, as preview one technique is to apply standard journalistic questions to the objects (nouns and noun phrases) in an ingested corpus, i.e. who, what, when, why, where, how. Applying this technique to an ingested history corpus might yield, “Who was General Grant?”

Of course, automatically generated queries could face the same quality and understanding problems that face the underlying ingestion process. To address this issue and gain a sense of the efficacy of this auto-query approach, we outline sampling techniques in which humans are used to assess both individual responses from the automated system, and statically estimate overall accuracy.

Details are in Section 4. However, as preview, one approach to human checking is to leverage crowd-source approaches like Amazon Mechanical Turk [2]. This approach can provide a measure of how humans view the quality of the auto-generated queries and added material. In all of these approaches, human feedback gives a sense of overall accuracy and helps detect areas where automated knowledge extraction and queries have gone awry.
2 Epistemology: How we know what we know

The dictionary defines *epistemology* as “a branch of philosophy that investigates the origin, nature, methods, and limits of human knowledge.” [4] That a branch of philosophy is dedicated to such investigation and understanding gives some hint of the challenge to algorithmic understanding of what is known about an ingested corpus.

Following this thought, raises the question, “What does it mean to ‘understand’ an input corpus, absent queries about it?” This inquiry might be viewed as a reformulation of the proverbial question, “If a tree falls in the forest and there is no one there to hear it, does it make a noise?” [7] However, this inquiry also raises the challenge of generating meaningful queries about a corpus absent any pre-existing knowledge of that corpus. For example, how can one formulate interesting questions about the US Civil War absent any predefined semantic knowledge about it?

That challenge is precisely what we propose to address. To be more specific, we propose a standardized mechanism for query generation that relies upon only two things: (1) the corpus itself in whatever form it has (traditionally human readable); and (2) well-known structural elements from the natural language of the corpus, e.g. English. For example, the system must know that set of verbs and the set of standard interrogatives.

Combining these two elements we propose a set of six automatic query-generation techniques outlined next in Sections 2.1 to 2.6. There are probably additional techniques for automatic query generation as well. However, these query generation techniques can generate a broad set of queries, largely independent of corpus or domain type. As such, they suggest a broad set of approaches that probably suffice to begin, and upon which we now elaborate.

2.1 Query Generation - Journalism Questions Applied to Objects

To every object (noun phrase) in the knowledge base, apply the standard questions taught every journalism student: *Who, what, why, when, where, how.*

For example, assume that the knowledge corpus has one statement, “General Grant was in the US Civil War.” This corpus references two objects: *General Grant* and *US Civil War*. As a result, using the *journalism questions* yields two sets of questions, the first about General Grant:

- **Who** was General Grant?
- **What** was General Grant? → *Prune*
- **Why** was General Grant? → *Prune*
- **When** was General Grant?
- **Where** was General Grant?
- **How** was General Grant?
The second set of questions is about the US Civil War:

- **Who** was the US Civil War? → *Prune*
- **What** was the US Civil War?
- **Why** was the US Civil War?
- **When** was the US Civil War?
- **Where** was the US Civil War?
- **How** was the US Civil War?

Despite their mechanical nature, it can be seen that most of these questions are quite reasonable. Indeed they are the sort of questions which if asked in a discussion between two people – e.g. a teacher and student – would yield not a direct answer, but a great deal of additional material, material upon which additional queries may be raised. For example, “When was General Grant?” might naturally lead to discussion of other events during the years of his life, such as the development of Maxwell’s Equations in Physics. Indeed, there are no bounds other than sum of human knowledge, and perhaps beyond.

In automated use, these questions and their follow-ups naturally lead to incorporation of material from additional corpuses (to get beyond our trivial, single-statement corpus of “General Grant was in the US Civil War”).

Of course, some of the auto-generated questions will be nonsensical, as flagged above with *Prune*. In Section 3 we discuss some rules and techniques for identifying and pruning such nonsensical queries. Section 4 goes further and explores how we might determine *sensible* queries, that are nonetheless not terribly useful.

### 2.2 Query Generation - Journalism Questions Applied to Object Pairs

In addition to generating queries on an input corpus by applying the *journalist questions* to every *object*, the journalist questions can be applied to every *object pair*, e.g.

- **When**: Was A after B?
- **Where**: Where is A located relative to B?
- **Who**: → ? → *Prune*
- **What**: → ? → *Prune*
- **Why**: Why did A ___ B?

  where ___ is a large set of verbs, and where again pruning is done for nonsensical items as will be described in Section 3. Two examples help clarify:


| Type 1  | Type 2  | Type 1  | Type 2  | Type 1  | Type 2  | Type 1  | Type 2  |
|---------|---------|---------|---------|---------|---------|---------|---------|
| Person  | Person  | Object  | Person  | Location| Person  | Concept | Person  |
| Person  | Object  | Object  | Object  | Location| Object  | Concept | Object  |
| Person  | Location| Object  | Location| Location| Location| Concept | Location|
| Person  | Concept | Object  | Concept | Location| Concept | Concept | Concept |

Table 1: Combinations of Object Pairs

- “Why did General Grant **fight** the US Civil War?”
- “Why did General Grant **eat** the US Civil War?” → Prune

**How**: Similar to **Why**: *How did A ___ B?*
where ___ is again a large set of verbs with pruning applied to nonsensical verbs, e.g.

- “*How did General Grant fight* the US Civil War?”
- “*How did General Grant eat* the US Civil War?” → Prune

### 2.3 Query Generation - Comparative Adjectives

There are additional techniques to automatically generate queries beyond the use of journalist questions. One such technique leverages comparative adjectives – an approach that has significant similarities to the object-verb-object case just discussed. For example:

- **Is A ___ B?**

  where ___ is the set of comparative adjectives, e.g. better, bigger, faster, older, closer, hotter, etc. These compare questions work well in conjunction with object type pairs, where all objects are broken into four types:

1. Person
2. Object
3. Location
4. Concept

Comparisons are generally meaningful when done between object pairs of the same type, i.e. the diagonal elements in Table 1. Comparisons across object types sometimes make sense as well – depending on the individual verb, as will be described in more detail in Section 3.
2.4 Query Generation - Analogies

The next technique for generating queries has similarities to the comparative adjective approach just discussed in Section 2.3. That technique is to generate queries based on analogies. For example,

“Who / what is most like object A?”

where object A may be a tree, a horse, the “French Revolution”, etc.

The answer to this question can also be checked in automated fashion via a Reverse check: Assume that Object B was returned in answer to the question about what is most like Object A. Then the following question can be posed to the system with the ingested corpus:

“Who / what is most like object B?”

Then an obvious check is whether object A is one of the top candidates from this query about object B.

There are cases where B may be most like A, but the relationship is not symmetric, and A is not most like B. However, the question acts as a filter in terms of what material is forwarded to more elaborate checks.

Those more elaborate – but still semi-automated checks could include things such as the use of Mechanical Turk on a subset of discovered analogies, as also suggested in [8].

2.5 Query Generation - Extensions to Analogies

Analogies as just described in Section 2.4 also yield two natural extensions – questions of the form:

1. “Why is that thing / person most like object A?”
2. “What is the evidence and reasoning for that choice?”

The second question in particular may require the ingested corpus to use DeepQA [1] or other techniques to provide appropriate evidence and reasoning for the answer to the first question.

2.6 Query Generation - Correlations

Similar to generating queries based on analogies, we can also generate questions based on determining what is most strongly correlated with object A. Not all objects are make sense as something on which to perform correlations, e.g. a kitchen table. For purposes of automatic query generation, correlations most obviously make sense for objects which are generally quantified, e.g. Oil Production. However, following the discussion in Section 2.3, correlations often make sense for objects of type Concept, e.g. War or Popularity. For instance, war may be correlated with other concepts such as border dispute or resource depletion.
3 Pruning Nonsensical Queries

Referring back to Section 2.1 and the sample questions about General Grant and the US Civil War, recall that three of the questions about objects in the corpus immediately seemed silly:

- **What** was General Grant? → *Prune*
- **Why** was General Grant? → *Prune*
- **Who** was the US Civil War? → *Prune*

Two straightforward ways to deal with all three of these queries are (a) simple grammatical rules; and (b) the object type classification described in Section 2.3, i.e., the classification of objects into *Person, Object, Location, Concept*. Use of (a) and (b) immediately yield a set of simple rules that can be used to prune these questions:

1. The question *what* does not fit with object type *Person*.
2. The question *who* does not fit with object types *Object, Location, Concept*.
3. The question *why* does not fit with object types *Person, Location*.

More generally, Table 2 lists a full set of pruning rules combining the journalist interrogatives and our four object types. This pruning based on grammatical structure and object types can be used beyond the *interrogative - object type* pairings in Table 2 and can be extended to the cases in Section 2.2 where we have queries involving questions about object pairs A and B in the corpus and of the form:

- **How** <Object A> - <Verb> - <Object B>?  
- **Why** <Object A> - <Verb> - <Object B>? 

As noted in Section 2.2, some queries of this form can be valuable probes, while others are nonsense:

- “*Why* did General Grant **fight** the US Civil War?”
- “*Why* did General Grant **eat** the US Civil War?” → *Prune*

To handle pruning of nonsensical questions involving such object pairs, we take a combined grammatical / semantic approach similar to that for single objects and which was summarized in Table 2. For object pairs, a much larger table results. Its structure is sketched in Table 3. Completing this table with all verbs from a specific language (e.g., English) requires significant manual effort. However, that effort is one-time and can then be applied any corpus or topic.
| Question | Object Type | Auto Prune? |
|----------|-------------|------------|
| Who      | Person      | Yes        |
| Who      | Object      | Yes        |
| Who      | Location    | Yes        |
| Who      | Concept     | Yes        |
| What     | Person      | Yes        |
| What     | Object      |            |
| What     | Location    |            |
| What     | Concept     |            |
| When     | Person      |            |
| When     | Object      |            |
| When     | Location    |            |
| When     | Concept     |            |
| Why      | Person      | Yes        |
| Why      | Object      | Yes        |
| Why      | Location    | Yes        |
| Why      | Concept     |            |
| Where    | Person      |            |
| Where    | Object      |            |
| Where    | Location    |            |
| Where    | Concept     | Yes        |
| How      | Person      |            |
| How      | Object      |            |
| How      | Location    |            |
| How      | Concept     |            |

Table 2: Pruning rules to eliminate nonsensical queries based on specific combinations of “journalist questions / interrogatives” and the four types into which we group objects.
Table 3: Pruning rules to eliminate nonsensical queries based on specific combinations of “Why” and “How” along with two objects from a corpus and a verb connecting those objects. The verb expands to a long list of verbs from the language of the corpus. Note that the form for pruning “How” is completely parallel to “Why” and omitted here for brevity.

An additional pruning mechanism is to assume any question for which all responses come back with low confidence [1] is a nonsense question. Such “low-confidence” questions could be tracked over time, and tagged as “nonsense” historically. This historical perspective allows determination of the frequency with which questions change over time from “nonsense” to “non-nonsense” – because with new knowledge, a high-confidence response emerges to a question previously assessed as nonsense due to low-confidence responses. The degree to which such classification changes occur gives an estimate of how many questions are incorrectly marked nonsense historically.

Even with this historical perspective, this method of pruning by confidence could result in missing key gaps in the corpuses and knowledge bases. Thus, the pruning rules outlined in Tables 2 and 3 may be a better initial approach, coupled with experimentation around confidence-based categorizations of questions.

4 Utility of Automatically Generated Queries

Even after pruning as described in Section 3, the techniques described in Section 2 naturally generate a very large set of queries on an ingested corpus. Beyond the need to form sensible queries as outlined in Section 3, it is also important to get a practical sense of the value of the queries in understanding the corpus. Some sensible queries may still yield “boring” results. For example, using queries with comparative adjectives as described in Section 2.3
we might generate the query, “Is a paper clip taller than a building?” The answer to this query could be useful in some analyses, but the query itself is unlikely to be asked by a human.

Of course, questions that may superficially or initially seem silly can reveal deep, interesting responses. For example, consider the auto-generated query, “Is lithium older than iron?” The answer turns out to be true, based on the development of the universe since Big Bang as described by Hoyle and others in the theory of Stellar Nucleosynthesis [9].

As both a theoretical and practical matter, it is helpful to know how many auto-generated queries are useful. In terms of theoretical value, knowing how many and which queries and query types yield useful responses is important in the development of further rules and heuristics to determine \textit{a priori} which auto-generated queries make sense. In terms of utilitarian value, having insight into how to prune is important in terms of keeping computation and storage tractable. Knowing the fraction of useful queries is also important for some of the techniques for checking results and filling gaps, as will be discussed in Section 5.

Section 3 suggested using confidence of responses to an auto-generated query as a measure of the query’s sensibility. This confidence measure can also be used as a measure of a query’s utility. Indeed, it is both an advantage and a drawback of this confidence method that for low confidence results, it may be difficult to disambiguate whether the cause was a nonsensical query or a boring query. (For high confidence results, the query was presumably both sensible and interesting.) Further research is needed to understand these distinctions and their underpinnings.

As outlined in the Introduction, approaches like Mechanical Turk [2] or Crowdflower [3] can also be used to check both sensibility and utility on a sample of auto-generated queries and their responses.

Another “human” oriented approach to checking the utility of auto-generated queries is to update or create Wikipedia entries when key missing information is detected, and where the cognitive system infers (with high confidence) that it has information to fill the gap. If these cognitive updates and entries pass muster with Wikipedia editors, then they are good. The cognitive system could even check periodically (a) if previously proposed updates have been maintained (i.e. the updated info was correct and useful); or (b) if previously proposed updates have been removed, i.e. the info was incorrect or unhelpful.

Both of these “human” approaches can yield statistical information about the fraction of auto-generated queries that are useful, as well as specific examples of such queries that are useful and not. However, these “human” approaches cannot broadly label all auto-generated queries into the desired three categories: (1) useful and interesting; (2) useful, but not interesting; and (3) nonsensical.

5 Filling Gaps Revealed by Auto Queries

As we have noted in several times previously, it is important to have some way to complete the cycle and fill-in incomplete data revealed by auto-generated queries. For two practical reasons, it is probably not feasible to auto-generate queries across all ingested corpuses of
1. Two of the automatic query generation techniques (i.e. the techniques in Sections 2.2 and 2.3) yield a number of queries that is quadratic in the number of total objects across all corpuses. Looking just at words in English, a quadratic function could yield a trillion object pairs, as [11] reported over 1 million English words. And not only are there many languages, but objects can be noun phrases and other complex arrangements.

2. Even if it is computationally tractable to handle the number of object pairs in (1), increased noise seems likely to result from considering all corpuses simultaneously when generating queries. For example, generating queries based on object pairs from a corpus on medieval poetry and a corpus on protein folding is unlikely to yield queries of high utility of the type outlined in Section 4. Aside from the computational problems noted in (1), having a high percentage of low-utility queries is likely to be a problem when humans evaluate query utility as also described in [4]. People frustrated by a high percentage of silly material are likely to provide lower quality checking than people reviewing results in which silly material is less common.

If practical considerations militate against generating queries from every pair of corpuses simultaneously, there is still the question of which sets of corpuses should be paired. A straight-forward (if somewhat dumb and unsophisticated) mechanism for making this determination is (a) to generate queries from every pair of corpuses and then (b) use measures of sensibility and utility from Sections 3 and 4 on the generated queries to determine which corpuses to pair. In other words, pair those corpuses that yield the highest percentage of useful queries.

Transitive closure could then be used to combine corpus pairs into corpus groupings with cardinality greater than 2. Such closure could stop when the percentage of useful queries between a pair of corpuses falls below a threshold. Of course, techniques other than query generation could be used in forming corpus groupings, as has been explored elsewhere [1].

Note also that the set of corpuses paired for generating queries need not be the same as the set of corpuses examined in fielding these queries. Indexing and tagging individual corpuses [19] may provide criteria by which corpuses are selected to resolve auto-generated queries.

A further wrinkle to the question of corpus merging arises from the fact that the corpuses themselves can change as a result of the query-generation process. More specifically, the pairing of auto-query generation and fielding those queries can create new enlarged corpuses in which particular pieces of information and their connections are explicitly noted – as opposed to requiring inference. At one level, this corpus merging and enlargement and explicit notation of connections could be considered “mere optimization”. However, this optimization is akin to humans learning a new piece of information and not needing to re-derive it every time it is needed. Such capability has clearly provided great benefit in the biological realm [20], e.g. as a means to reduce energy requirements for an organism, and
thus reduce food needs. In biology this learning capability can also provide faster response
time, thus allowing escape from a dangerous situation that would not otherwise be possible.
As such, it seems plausible that such optimization will have similar value here.

As noted in the Introduction, this amalgamation of corpuses and corresponding learning
process also mirrors the human research endeavor: understand material, look elsewhere when
key questions are not answered, then pursue new questions revealed by additional knowledge.

As with human research and the scientific method [21], another component of completing
this cycle of query generation and fielding those queries is to maintain historical confidence
levels for inferences. Then periodically look for new information that would increase or
decrease confidence in those inferences.

The most effective combination of techniques and heuristics to use for completing this
cycle of query generation and query response is a subject of further research.

6 Measuring Capability and Changes to It

With all of the capabilities described in the previous sections, it would be useful to have
simple, high-level measures of overall capability and changes to it. Following the lead of [1],
we focus on a pair of measures: (a) breadth of coverage and (b) precision. (a) Breadth
of coverage is the percentage is auto-generated queries for which the system can provide a
high-confidence reply. (b) Precision measures the percentage of all attempted responses in
(a) which are correct.

Unlike IBM’s Watson playing Jeopardy [1], precision itself is a fuzzy measure in this realm,
since there is no answer book which says for all queries whether the given response is correct.
Thus precision must be determined by some combination of other means. Thankfully, we do
not need an exact measure of precision to get a general sense of how the system is performing,
and the degree to which it is improving or degrading over time.

Human-based techniques described in Section 4 and leveraging Mechanical Turk, Wikipedia,
etc provide one set of baselines – with Mechanical Turk perhaps giving a sense of average
human ability in a particular domain and Wikipedia giving a sense of more expert human
ability. For topics of special importance, domain experts could be recruited or contests held,
a la Jeopardy – perhaps handicapping the automated system by limiting it to a “small”
amount of training time.

All of these approaches allow some answer to key questions about our proposed system:
(1) can it answer as many questions as a human or more, (2) can it do it with equal or
greater precision, and (3) can it do so in equal or shorter time?

External benchmark questions could also be used for these measurements such as from
the Stanford QA DB [22]. Such benchmark questions should of course be applied after our
proposed system has trained itself on auto-generated queries and an enlarging set of corpus
material, as outlined in Section 5.
7 Related Work

Previous work on automatic query generation has largely focused on specialized domains. For example, [12], “generate web-search queries for collecting documents matching a minority concept.” [13] explore, “interactive construction of natural language queries.” [14] process patent applications looking for terms that can be used to generate queries automatically. [15] automatically generate queries based on “keywords expanded from [a] user input keyword, ... by selecting candidate keywords and assigning weight value[s] to each candidate keyword from [a] semantic thesaurus and document keyword list.” Unlike the approach described here, the approach of Ryu et al requires some domain knowledge on the part of the user. None of these other works address automatic generation of queries for a general corpus on arbitrary topics and in arbitrary format.

There is a good deal of work that uses grammatical structure for pruning as discussed in Sections 3 and 4. For example, [16] prune noun phrases. [17], “present a hybrid method for text summarization, combining sentence extraction and syntactic pruning.” However, these works focus primarily on identification of particular grammatical artifacts and reduction of corpus size, as opposed a more semantic view of comprehending content, as proposed here. Broader measures of confidence and pruning were well explored in [1].

The epistemology approach described in Section 4 is most closely related to [18]. That paper, “studies what kinds of facts about the world are available to an observer with given opportunities to observe, how these facts can be represented in the memory of a computer, and what rules permit legitimate conclusions to be drawn from these facts.” As such it focuses more on what is knowable versus the focus here on understanding and expanding what has been ingested.

The techniques described here can be viewed as a combination of supervised and unsupervised learning techniques. In particular, the cycle of auto-query generation / find missing material / auto-query generation on expanded corpus / etc is a form of unsupervised learning, which dates to [23]. Unlike that work and its successors, the approach here is not based on a neural nets or statistical approaches, but a variety of grammatical and semantic techniques applicable to unstructured content such as text. Techniques described in Section 4 where results are reviewed by humans, represent an offline form of supervised learning. Like unsupervised approaches, much of the existing supervised literature focuses on neural nets, as typified by [24] on back-propagating errors.

Aside from supervised and unsupervised learning, most learning applications focus on specific domains, e.g. [25] [26] or learning representations, e.g. [27] [28]. Our techniques are cross-domain, and do not focus or require particular representations.

[29] discuss learning by crowd sourcing, which has similarities to techniques in Section 4 using Mechanical Turk. [30] [31] have proposed a set of techniques to write Wikipedia articles automatically. However, their approach is based on finding similar articles, abstracting and summarizing them, and then using that representation to generate Wikipedia articles, or additions to existing articles. By contrast, our approach looks for missing material (via the auto-generated queries) and adds it to Wikipedia.
8 Conclusions

We have described techniques to generate queries automatically based on one or more ingested, input corpuses. These queries can then be used to test the efficacy of ingestion – how much does the system really know. Since the queries are automatically generated, neither their generation nor testing of ingestion based on the queries requires human experts.

By removing the human factor, this approach allows more effective scaling of AI and cognitive capabilities and more rapid deployment to new domain areas. By means of the generated queries, this approach also provides a means to identify and remedy problem areas in ingestion. The proposed techniques also allow knowledge to be extended naturally, and for tests of capability.

Proving the approaches outlined here is, of course, essential, and we look forward to reporting the results of such investigations.

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