

ChatGPT for the Petroleum Industry

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Gulf Coast Section



Gulf Coast Section

ChatGPT for the Petroleum Industry

- Goal with this talk: Showing how ChatGPT can be used with two use cases
- But first, what is ChatGPT and why is everyone wild about it?
- What's a strategy for using ChatGPT? (last-mile analogy)
- Use case 1: Question answering for SPE
- Use case 2: Question answering using our Oilfield Places™ knowledge graph
- Use case N (WIP): Generating insights about documents

ChatGPT in an Nutshell

- ChatGPT is a "large language model" (LLM)
 - There are others: BERT and derivatives, Bard, LLaMA, BioGPT, GPT-3, GPT-4, ...
- G.P.T:
 - G = Generative: it predicts (generates) the next word in a block of text
 - P = Pre-trained: before it's deployed for some specific task, it has already trained how to predict the next word on terabytes of text (i.e., much of the public internet)
 - T = Transformer: the type of neural net used; has the ability to understand words by looking at ("attending to") previous words to establish context
- History (in AI, one year feels like 10):
 - 2017:
 - "Attention is All You Need" (70k citations)
 - 2018:
 - "BERT: Pre-training of deep bidirectional transformers for language understanding" (63k citations)
 - 2019:
 - GPT-2 released
 - 2020:
 - "Large language models are few-shot learners" (9k citations)
 - GPT-3 released
 - 2022:
 - "Training language models to follow instructions with human feedback" (400 citations) - InstructGPT model
 - November 2022:
 - ChatGPT released (improved InstructGPT model)
 - March 2023:
 - GPT-4 released

ChatGPT in an Nutshell

HOW LONG IT TOOK TOP APPS TO HIT 100M MONTHLY USERS

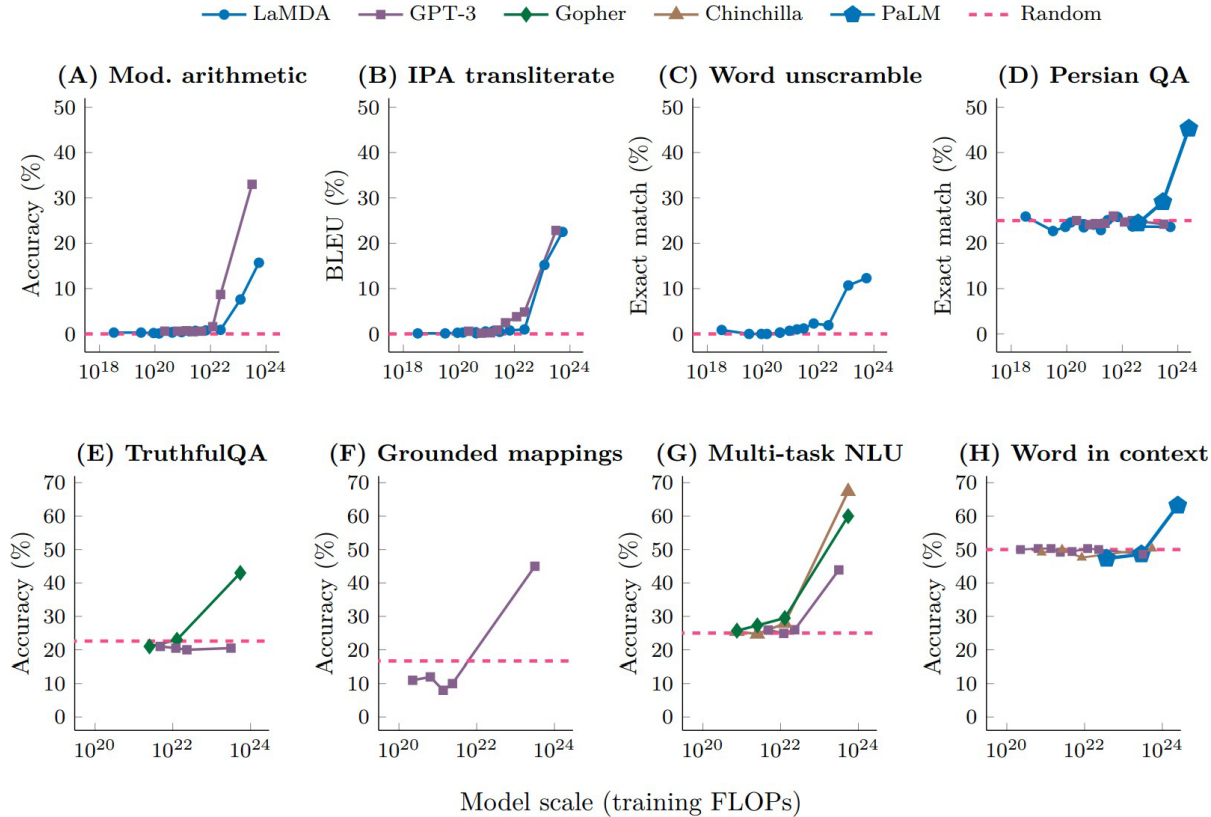
ChatGPT is estimated to have hit 100M users in January, 2 months after it's launch. Here's how long it took other top apps to reach that:



SOURCE: UBS

yahoo!
finance

ChatGPT in an Nutshell



Wei, Jason, et al. "Emergent abilities of large language models."
arXiv preprint arXiv:2206.07682 (2022).

Sébastien Bubeck
Sr. Principal Research
Manager in the Machine
Learning Foundations group
at Microsoft Research
AAAI Conference 2023



THE question

How does *intelligence* emerge from:

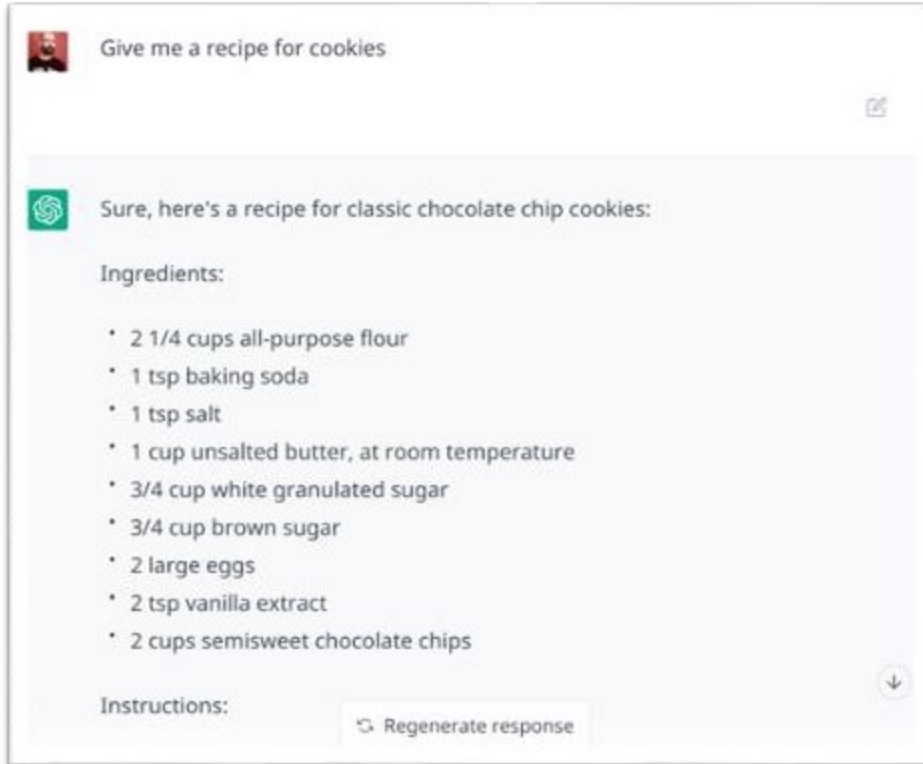
- ▶ gradient-descent based training to do next-word prediction
- ▶ on a large dataset (say 1T tokens)
- ▶ with a large transformer (say 100 layers, 100 heads, 10k-ish dimensional embedding)

The truth is that nobody has a clue what's going on!!!

I think nobody on the planet has a clue
about what's going on just just nobody

Strategy for Using ChatGPT Effectively

Option A



Give me a recipe for cookies

Sure, here's a recipe for classic chocolate chip cookies:

Ingredients:

- 2 1/4 cups all-purpose flour
- 1 tsp baking soda
- 1 tsp salt
- 1 cup unsalted butter, at room temperature
- 3/4 cup white granulated sugar
- 3/4 cup brown sugar
- 2 large eggs
- 2 tsp vanilla extract
- 2 cups semisweet chocolate chips

Instructions:

Regenerate response

Option B

Use the API. Make it part of a processing workflow.

```
import openai

openai.ChatCompletion.create(
    model="gpt-3.5-turbo",
    messages=[
        {"role": "system", "content": "You are a helpful assistant."},
        {"role": "user", "content": "Who won the world series in 2020?"},
        {"role": "assistant", "content": "The Los Angeles Dodgers won the"},
        {"role": "user", "content": "Where was it played?"}
    ]
)
```

Model	Prompt	Completion
8K context	\$0.03 / 1K tokens	\$0.06 / 1K tokens
32K context	\$0.06 / 1K tokens	\$0.12 / 1K tokens

ChatGPT is the "last mile"

Your dataset - the answer is *somewhere*



Your existing tools can find a *close* answer



ChatGPT can take these close answers and deliver *the best* answer



<https://www.gousspack.com/final-mile-large-parcel-carriers-take-on-the-heavy-lifting-of-peak-season/>

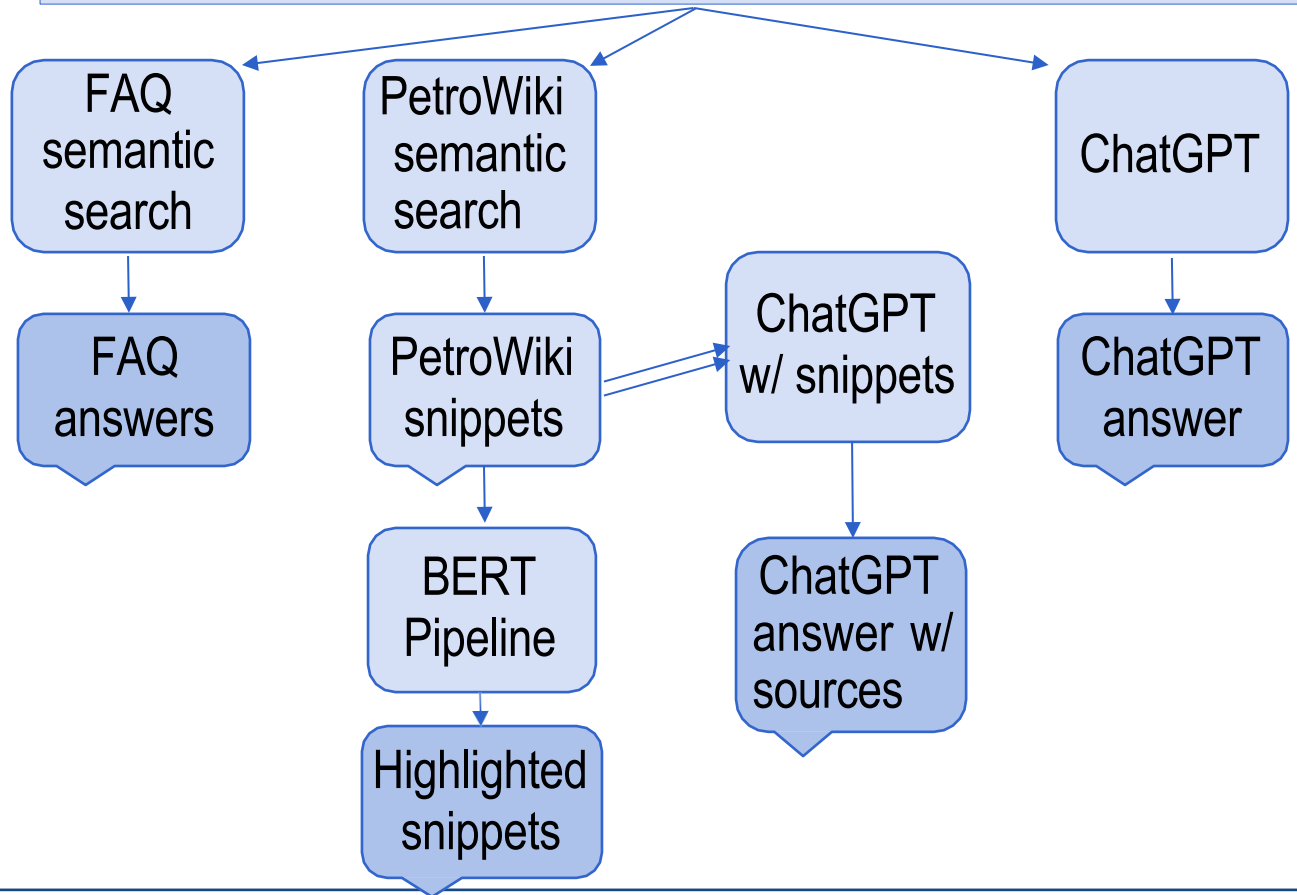
<https://www.nytimes.com/2014/12/22/business/crunch-time-for-fedex-and-ups-as-last-minute-holiday-shipping-ramps-up.html>

Use case 1: Question answering for SPE

Experiment conducted March 16 to April 16, 2023

SPE Question-Answering

Question: "Has anyone had success determining fracture dimensions?"



SPE Question-Answering

Question



Has anyone had success determining fracture dimensions?

For each question, order the answers via the drag and drop arrow on the left side of each answer, based on the answer's quality, with the top of the list answer with the highest quality.

ChatGPT

Rank:
↓
1

Yes, according to the context, fracture dimensions can be determined by using models to make decisions and by analyzing fracture-treatment data. The design must always compare actual results with the predictions from model calculations. By "calibrating" the 2D model with field results, the 2D models can be used to make design changes and improve the success of stimulation treatments. Smith et al. discussed other issues and presented several case histories in which fracture-treatment data were analyzed to determine the propped fracture dimensions.

BERT Pipeline

Rank:
↓
2

Smith et al. discussed other issues and presented several case histories in which fracture-treatment data were analyzed to determine the propped fracture dimensions. Smith stated that **fracture height growth during and after pumping operations, fluid loss in layered formations, and slurry viscosity all affect the propped fracture dimensions.**

- [Read more here](#)

Source citation

SPE Question-Answering

Question



What is cumulative production?

For each question, order the answers via the drag and drop arrow on the left side of each answer, based on the answer's quality, with the top of the list being the answer with the highest quality.

FAQ

Rank:
↓
1

gross production

[- Read more here](#)

PetroWiki
Snippets
through
ChatGPT

Cumulative production refers to the total amount of hydrocarbon that has been recovered up to a certain date. It includes all the recoverable resources that have been estimated and the production that has been measured in terms of sales product specifications. Raw production quantities, including non-hydrocarbons, are also measured to support engineering analyses requiring reservoir voidage calculations. Multiple development projects may be applied to each known or unknown accumulation, and each project will be forecast to recover an estimated portion of the initially-in-place quantities.

[- Read more here](#)

Source citation

SPE Question-Answering Results

	Conversation	Snippets	Canned	More Knowledge	Less Knowledge	Sources	No Sources
FAQ			X		X	X	
BERT Pipeline		X			X	X	
PetroWiki Snippets through ChatGPT	X				X	X	
ChatGPT	X			X			X

SPE Question-Answering

Questions Created: 36 Questions Validated: 3

Leader Board

Question

Has anyone had success determining fracture dimensions?

For each question, order the answers via the drag and drop arrow on the left side of each answer, based on the answer's quality, with the top of the list being the answer with the highest quality.

Rank 1: Yes, according to the context, fracture dimensions can be determined by using models to make decisions and by analyzing fracture-treatment data. The design must always compare actual results with the predictions from model calculations. By "calibrating" the 2D model with field results, the 2D models can be used to make design changes and improve the success of stimulation treatments. Smith et al. discussed other issues and presented several case histories in which fracture-treatment data were analyzed to determine the propped fracture dimensions.

Rank 2: Smith et al. discussed other issues and presented several case histories in which fracture-treatment data were analyzed to determine the propped fracture dimensions. Smith stated that **fracture height growth during and after pumping operations, fluid loss in layered formations, and slurry viscosity all affect the propped fracture dimensions.**

Rank 3: The figure illustrates how such an analysis can alter the desired fracture length. Finally, **after the optimum, risk-adjusted fracture treatment has been designed, it is extremely important to be certain the optimum design is pumped correctly into the well.** For this to occur, the operator and the service company should work together to provide quality control before, during, and after the treatment is pumped.

Rank 4: For example, **one in every five fracture treatments in a certain formation is not successful;** therefore, 80% of the expected revenue and 100% of the expected costs can be used to determine the optimum fracture length. The figure illustrates how such an analysis can alter the desired fracture length. Finally, after the optimum, risk-adjusted fracture treatment has been designed, it is extremely important to be certain the optimum design is pumped correctly into the well.

Rank 5: By "calibrating" the 2D model with field results, the 2D models can be used to make design changes and improve the success of stimulation treatments. **If the correct fracture height value is used in a 2D model, the model will give reasonable estimates of created fracture length and width of other parameters, such as in-situ stress, Young's modulus, formation permeability, and total leakoff coefficient, are also reasonably known and used.** To illustrate how certain variables affect fracture propagation, the equations conform to the PKN fracture geometry assumptions.

Rank 6: Yes, there have been successful methods developed for determining fracture dimensions in the petroleum industry. One common method is through the use of microseismic monitoring, which involves placing sensors in the surrounding rock to detect and locate microseismic events that occur during hydraulic fracturing. By analyzing the location and magnitude of these events, engineers can estimate the size and orientation of the fractures created during the fracturing process. Other methods include pressure transient analysis and tracer testing. These techniques are important for optimizing well performance and maximizing oil and gas recovery.

Non Relevant Answers Below

Rank: N/R

The key is to use models (any model) to make decisions, rather than trying to calculate precise values for fracture dimensions. **The design must always compare actual results with the predictions from model calculations.** By "calibrating" the 2D model with field results, the 2D models can be used to make design changes and improve the success of stimulation treatments.

Submit Ranking

Create Question Next Question

Number of unique users: 103

Number of unique users who ranked answers: 86

Number of unique users who created questions: 31

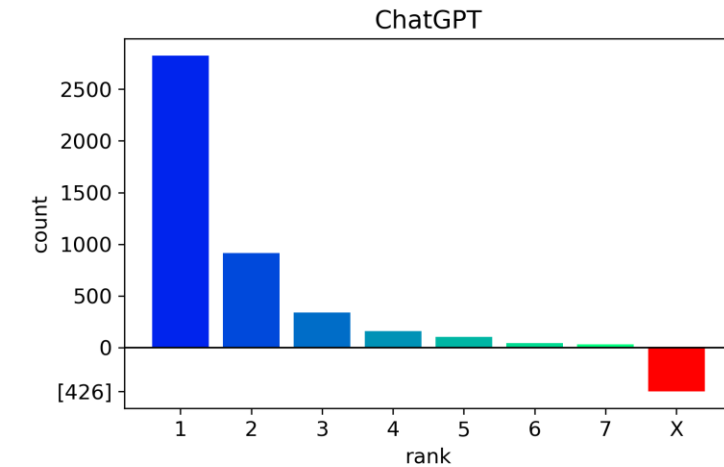
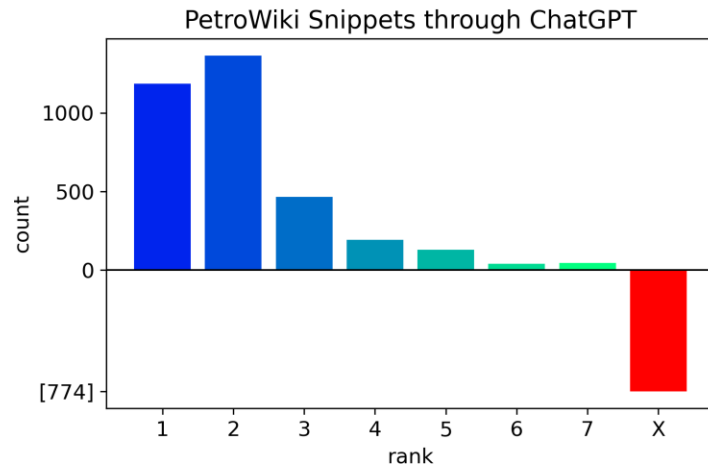
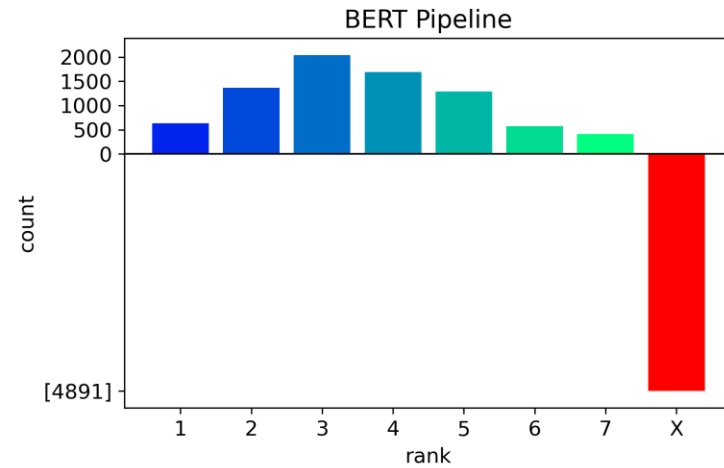
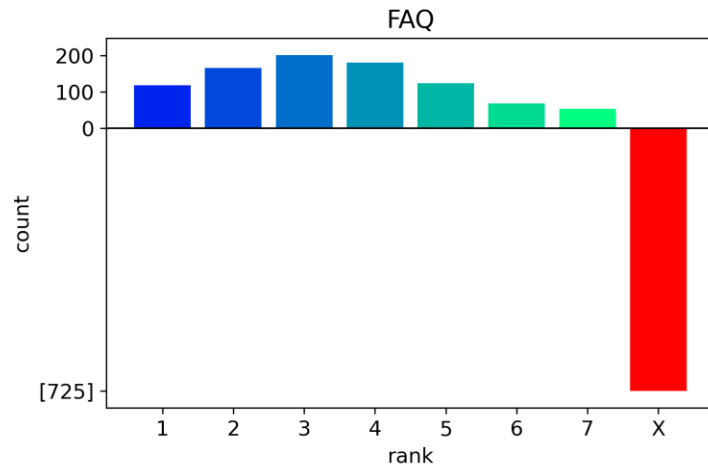
Country	Questions Created
Algeria	11
Azerbaijan	1
India	18
Italy	1
Kuwait	8
Nigeria	50
Oman	2
Saudi Arabia	5
United States	208

SPE Question-Answering

Country	Answers Ranked
Algeria	73
Australia	21
Azerbaijan	34
Brazil	1
Canada	19
Egypt	12
France	7
Gabon	55
India	237
Indonesia	6
Italy	134
Japan	3

Country	Answers Ranked
Kuwait	222
Malaysia	56
Netherlands	6
Nigeria	291
Oman	6
Pakistan	5
Qatar	18
Saudi Arabia	51
Sweden	50
United Arab Emirates	34
United Kingdom	106
United States	834

SPE Question-Answering Results



SPE Question-Answering Results

Form

- Conversational answers > highlighted snippets

Content

- More knowledge > less knowledge

Sourcing

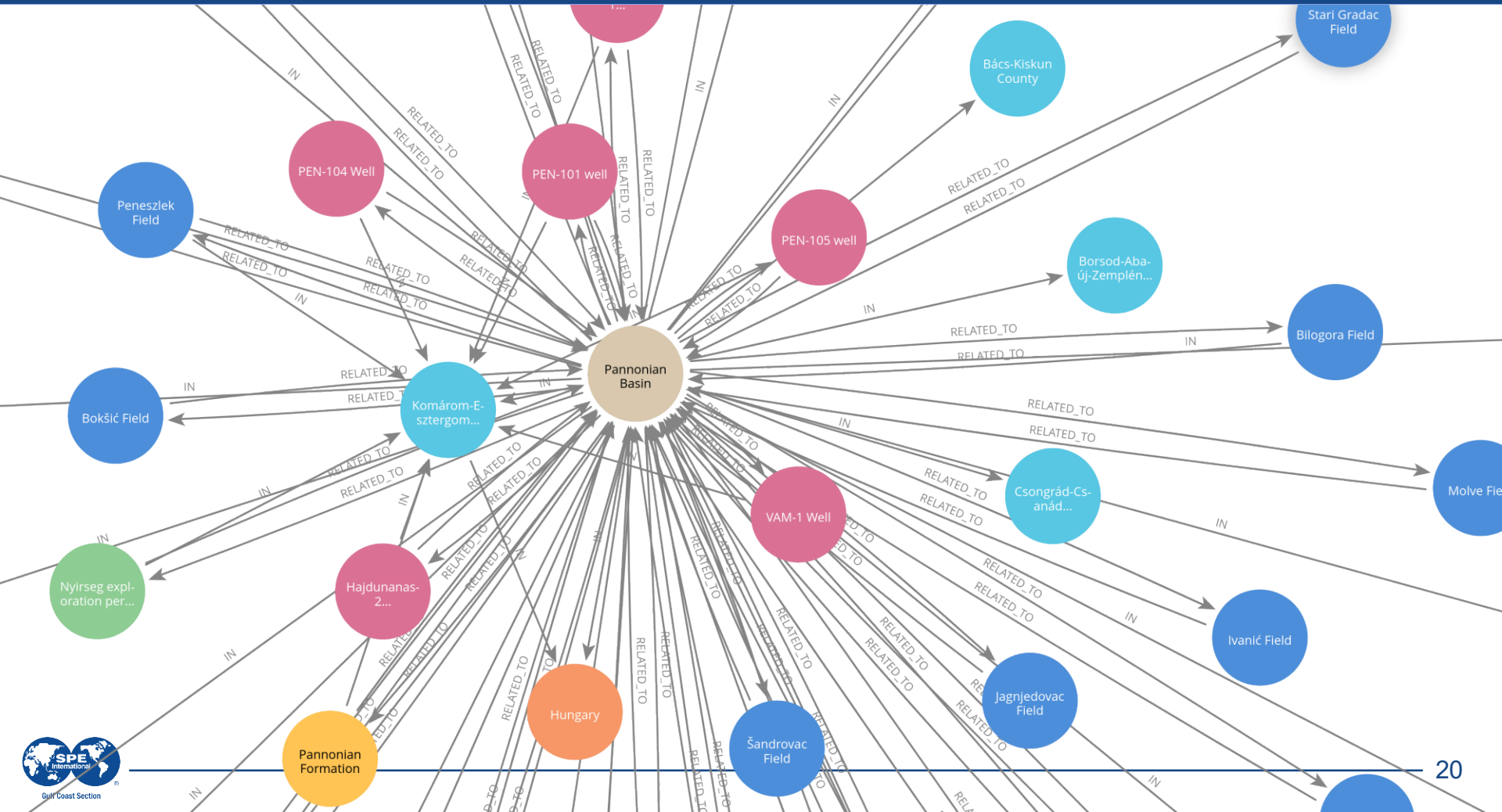
- Citing sources \approx not citing sources

SPE Question-Answering Next Steps

- Train on OnePetro and SPE Connect content
 - Wider breadth, deeper knowledge, support for “how to questions”
- Direct volunteers to ask real-world “**how to**” and “**solve a problem**” questions
- Gather and Analyze results

Use case 2: Question answering using our Oilfield Places™ knowledge graph

Answering Queries with a Knowledge Graph



Answering Queries with a Knowledge Graph

Strategies for using ChatGPT (GPT-4) for answering queries with a knowledge graph:

- Describe the graph in English and then ask the query.
- Describe the graph in structured form and then ask the query.

Answering Queries with a Knowledge Graph

English:

There is a Neo4j Graph Database.

It has nodes with the labels Continent, Region, Country, Country_Region, and County; all these nodes have the property “name.” Country_Region nodes also have the property “type,” which is always either “Land” or “Water.” All Region nodes have an INTERSECTS relationship pointing to Continent nodes. All Country nodes have an IN relationship pointing to Continent nodes. Some Country nodes have an IN relationship pointing to Region nodes. Country_Region nodes have relationships pointing to other Country_Region nodes; the label of the relationship between Country_Region nodes is conditional on the “type” property of these nodes. If either Country_Region node has type=Water, then the relationship label is NEAR, otherwise it is IN. County nodes have an IN relationship pointing to other County nodes. County nodes can have an IN relationship to Country_Region, Country, Continent, or Region nodes depending on the situation. Country_Region nodes can have an IN relationship to Country, Continent, or Region nodes depending on the situation. There are also “oilfield” nodes with the labels Basin, Formation, Leasing_Area, Block, and Field; all these nodes have the property “name.” Each of these “oilfield” nodes can have an IN relationship to a node with the same label, any other of the “oilfield” nodes, as well as County, Country_Region, Country, Continent, and Region nodes. There are Well nodes, with the property “name,” that can have an IN relationship to Basin, Formation, Leasing Area, Block, and Field nodes.

Answering Queries with a Knowledge Graph

Structured schema:

```
[
  {
    "value": {
      "Geopolitical": {
        "relationships": {
          "MAPPED_TO": {
            "direction": "out",
            "labels": [
              "Mapped_Term"
            ]
          },
          "RELATED_TO": {
            "direction": "out",
            "labels": [
              "Field",
              "Oilfield",
              "Block",
              "Basin",
              "Formation",
              "Leasing_Area",
              "Basin",
              "Leasing_Area",
              "Block",
              "Field",
              "Formation",
              ...
            ]
          }
        }
      }
    }
  }
]
```

The schema can be exported from Neo4j.

Our current Oilfield Places™ knowledge graph has:

- 154k nodes
- 477k "MAPPED_TO" relationships (terms that identify places)
- 233k "RELATED_TO" relationships (e.g., basin is related to field but one is not "inside" the other)
- 89k "IN" relationships (mostly geopolitical and wells, strict containment)

Answering Queries with a Knowledge Graph

Given a user's query: "**List the wells and their corresponding type that are in Texas.**"

We prompt GPT-4 as follows:

Given this graph, return the cypher query to the question below. Only give the cypher query, no explanation.

[English description of graph or schema listing]

Question: List the wells and their corresponding type that are in Texas.

Answering Queries with a Knowledge Graph

The response is a Neo4j cypher query.

We try to run it. If it succeeds, we get a Neo4j result.

```
MATCH (w:Well)-[:IN]->(cr:Country_Region {name: 'Texas'})  
RETURN w.name as Well, w.type as Type
```

```
[{'Well': 'Breitling-Turner #2 Well', 'Type': 'oil&gas'}, {'Well': 'Breitling-Turner #1 Well', 'Type':  
'oil&gas'}, ...]
```

We can optionally query GPT-4 again for a nice summary of these data.

The wells in Texas are as follows:

- Breitling-Turner #2 Well - Type: Oil & Gas
- Breitling-Turner #1 Well - Type: Oil & Gas
- ...

Answering Queries with a Knowledge Graph

More examples:

"Is the Sequoia Field onshore or offshore?"

```
MATCH (f:Field {name: 'Sequoia Field'})-[:IN]->(cr:Country_Region) RETURN cr.type as Onshore_Offshore
```

```
[{'Onshore_Offshore': 'Water'}]
```

"Which fields are in Queensland and what are their leasing areas and basins?"

```
MATCH (f:Field)-[:IN]->(cr:Country_Region {name: 'Queensland'}), (f)-[:RELATED_TO]->(la:Leasing_Area), (f)-[:RELATED_TO]->(b:Basin) RETURN f.name as Field, la.name as Leasing_Area, b.name as Basin
```

```
[{'Field': 'Scotia Field', 'Leasing_Area': 'PL 176', 'Basin': 'Surat-Bowen Basin'}, {'Field': 'Scotia Field', 'Leasing_Area': 'PL 176', 'Basin': 'Bowen Basin'}, ...]
```

Answering Queries with a Knowledge Graph

Subtle errors and "hallucinations":

"Which fields in Australia are in Queensland and what are their leasing areas and basins?"

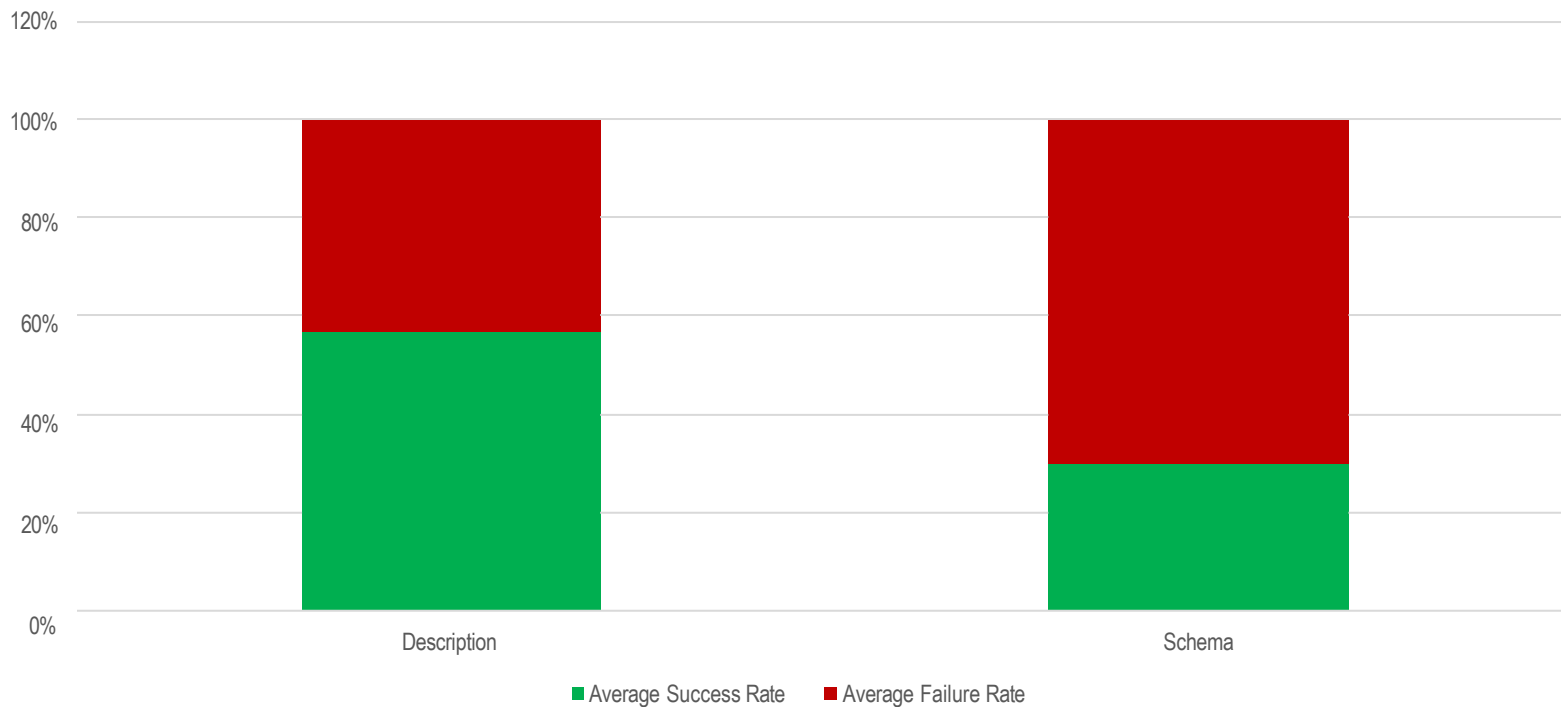
```
MATCH (f:Field)-[:IN]->(cr:Country_Region {name: 'Queensland'}), (f)-[:IN]->(la:Leasing_Area), (f)-[:IN]->(b:Basin), (cr)-[:IN]->(c:Country {name: 'Australia'}) RETURN f.name as Field, la.name as Leasing_Area, b.name as Basin
```

"Which fields are in Queensland, Australia and what are their leasing areas and basins?"

```
MATCH (f:Field)-[:IN]->(cr:Country_Region {name: 'Queensland', type: 'State'})-[:IN]->(c:Country {name: 'Australia'}) OPTIONAL MATCH (f)-[:RELATED_TO]->(la:Leasing_Area) OPTIONAL MATCH (f)-[:RELATED_TO]->(b:Basin) RETURN f.name as Field, la.name as Leasing_Area, b.name as Basin
```

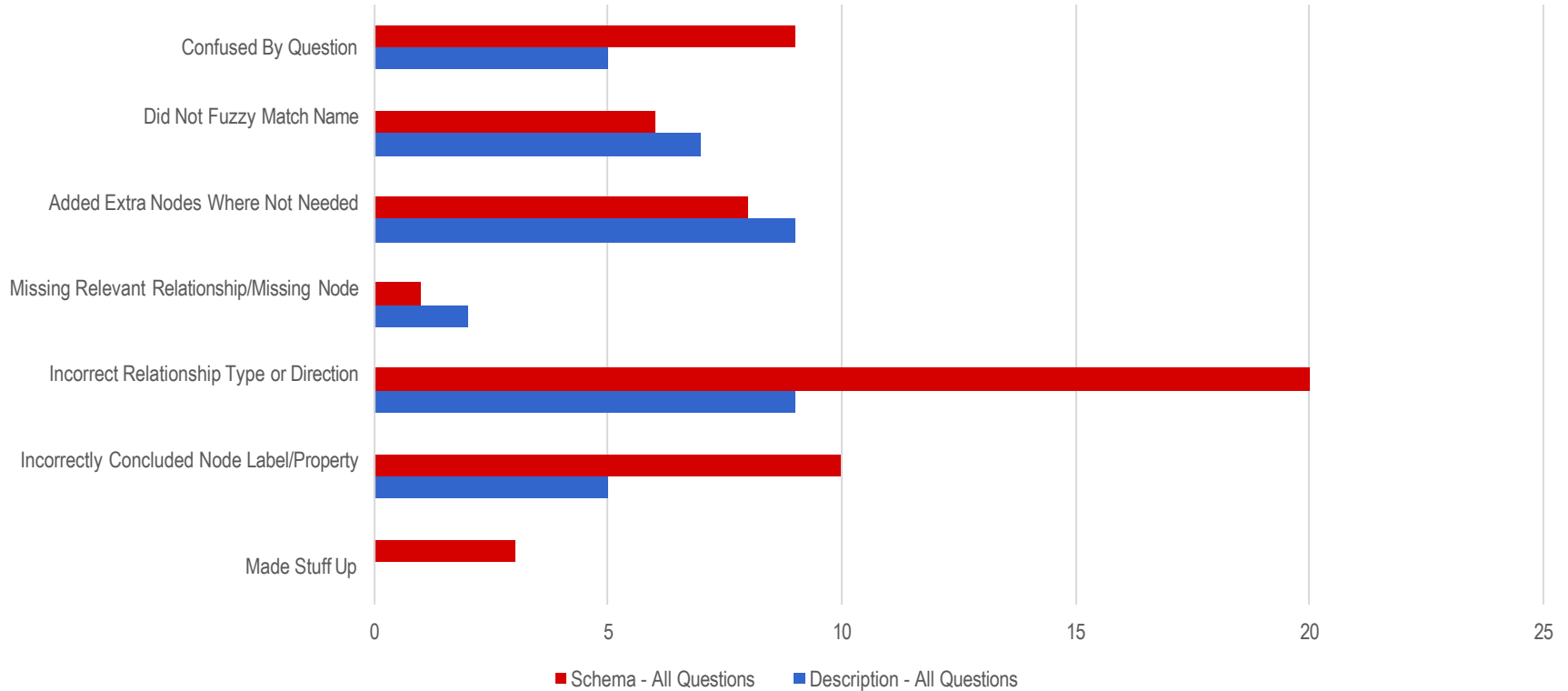
Answering Queries with a Knowledge Graph - Results

Description vs. Schema Context
on Average



Answering Queries with a Knowledge Graph - Results

Failure Reasons - All Questions



Answering Queries with a Knowledge Graph - Takeaway

In the aggregate, the model performed worse when using the schema, rather than our description, as context.

However, we can investigate what the schema did well, and integrate these lessons learned into the description we provide.

We can provide examples to GPT-4 for hard cases: "For example, if asked, '...' respond '...'"

We can also use GPT-4's hallucinations to guide us as we expand the knowledge graph:

"Do any of the offset wells in the Platanal Field or Pimienta Formation have reservoir tests with fluid samples?"

```
MATCH (w:Well)-[:RELATED_TO]->(:Field {name: 'Platanal Field'})-[:RELATED_TO]->(r:Reservoir Test)-[:HAS]->(f:Fluid Sample) WHERE w.offset = true RETURN w.name, r, f
```

UNION

```
MATCH (w:Well)-[:RELATED_TO]->(:Formation {name: 'Pimienta Formation'})-[:RELATED_TO]->(r:Reservoir Test)-[:HAS]->(f:Fluid Sample) WHERE w.offset = true RETURN w.name, r, f
```

Use case N (WIP): Generating insights about documents

Document Insights

Home > [Clean fuel](#) >

Jiangnan Shipyard receives \$470 million order for two LNG carriers

VESSELS

March 28, 2023, by Ajsa Habibic

Jiangnan Shipyard, a subsidiary of China State Shipbuilding Corporation (CSSC), has entered into shipbuilding contracts with compatriot insurance conglomerate China Taiping Insurance Holdings for the construction of two LNG carriers.



Companies mentioned:

- Jiangnan Shipyard (Shipbuilding Company)
- China State Shipbuilding Corporation (CSSC) (Shipbuilding Company)
- China Taiping Insurance Holdings (Insurance Conglomerate)
- Taiping & Sinopec Financial Leasing (TSFL) (Financial Leasing Company)
- Taiping 26 (Subsidiary)
- Taiping 27 (Subsidiary)
- Shandong Marine Energy (SDME) (Marine Energy Company)
- ADNOC Logistics & Services (Shipping and Maritime Logistics Company)
- ADNOC (Oil and Gas Company)
- GTT (French Containment Specialist Company)

Document Insights

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Knowledge graph triples:

- (Jiangnan Shipyard, type, shipyard)
- (Jiangnan Shipyard, located_in, China)
- (Jiangnan Shipyard, subsidiary_of, China State Shipbuilding Corporation)
- (China State Shipbuilding Corporation, type, corporation)
- (China Taiping Insurance Holdings, type, insurance_conglomerate)
- (China Taiping Insurance Holdings, located_in, China)
- (Taiping & Sinopec Financial Leasing, located_in, China)
- (Shandong Marine Energy, type, company)
- (Shandong Marine Energy, located_in, Singapore)
- (LNG Carrier, capacity_cbm, 175000)
- (Shipbuilding Contract, worth, 470000000)
- (Bareboat Charter Agreement, type, agreement)
- (Bareboat Charter Agreement, duration_months, 180)
- ...

Document Insights

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Simplified facts:

- Jiangnan Shipyard is a subsidiary of China State Shipbuilding Corporation (CSSC).
- Jiangnan Shipyard has entered into shipbuilding contracts with China Taiping Insurance Holdings.
- The shipbuilding contracts are for the construction of two LNG carriers.
- China Taiping Insurance signed the contracts through its subsidiaries, Taiping & Sinopec Financial Leasing (TSFL) and Taiping 26 and Taiping 27, on 27 March.
- The contracts are worth \$470 million.
- Jiangnan Shipyard will build two LNG carriers with a capacity of 175,000 cbm each.
- The delivery dates for the vessels are March and July 2027.
- ...

Document Insights

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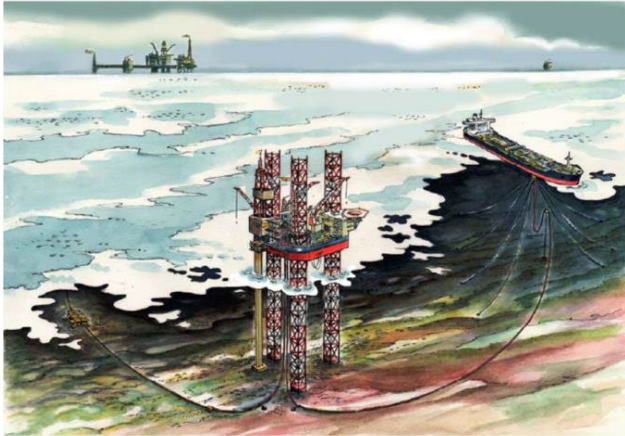


Generated FAQs:

1. What is the value of the order Jiangnan Shipyard received for the construction of two LNG carriers?
 - The order is worth \$470 million.
2. Who are the parties involved in the shipbuilding contracts and charter agreements?
 - Jiangnan Shipyard, China Taiping Insurance Holdings, Taiping & Sinopec Financial Leasing (TSFL), Taiping 26, Taiping 27, and Singapore-based Shandong Marine Energy (SDME) are involved in the contracts and agreements.
3. When are the two LNG carriers expected to be delivered?
 - The vessels are due for delivery in March and July 2027.

Document Insights

Individual Well Drilling Program Well 15/9-F-14



Volve
Rev. 0

Title:

- Individual Well Drilling Program: Well 15/9-F-14
 - A detailed report on the drilling program for the Hugin oil producer well in Volve

Type:

- This document is an Individual Well Drilling Program for Well 15/9-F-14 in the Volve field.

Summary:

- This document is an individual well drilling program for well 15/9-F-14 in the Volve field, with a focus on drilling procedures, health and safety, and contingency plans. It includes information on the drilling rig, well status, directional correction data, geology, dispensations, and drilling procedures for various hole sections. The document also includes appendices with figures, tables, and abbreviations.

Document Insights

General well data

Drilling rig: Mærsk Inspirer
License number: PL 046BS
Well name: 15/9-F-14
Slot: 14
Type of well: Hugin oil producer
Water depth /air gap: 91 m / 54.9 m
Subsea Wellhead: Planned 140 m to top 20" wellhead housing
Surface Wellhead: Planned 21.4 m to bottom surface wellhead (multibowl)

Planned structure centre coordinates (at subsea wellhead level):

Geographic: Lat. 58° 26'29,807" N Long. 1° 53'14,929" E
UTM: 6 478 563.52 m N 435 050.02 m E

Planned slot centre coordinates (at subsea wellhead level):

Geographic: Lat. 58° 26'29,769" N Long. 1° 53'15,079" E
UTM: 6 478 562,31 m N 435 052,44 m E
Rectangular: -1,21 m N 2,42 m E (from structure centre)

Target: Ref. RTD section 4.1.
Well Status: Guiding template positioned and 30" conductor set.

Depth reference:
 All depths from RT (Rotary Table) unless otherwise stated.

Account:
Drilling network: 944509
Drilling WBS: L.O046V.002.2A01B01

Fact	Description
License no.	PL 046BS
Well	15/9-F-14
Drilling rig	Mærsk Inspirer
Type of well	Hugin oil producer
Water depth /air gap	91 m / 54.9 m
Subsea Wellhead	Planned 140 m to top 20" wellhead housing
Surface Wellhead	Planned 21.4 m to bottom surface wellhead (multibowl)
Planned structure centre coordinates (at subsea wellhead level)	Geographic: Lat. 58 26'29,807" N Long. 1 53'14,929" E UTM: 6 478 563.52 m N 435 050.02 m E
Planned slot centre coordinates (at subsea wellhead level)	Geographic: Lat. 58 26'29,769" N Long. 1 53'15,079" E UTM: 6 478 562,31 m N 435 052,44 m E Rectangular: - 1,21 m N 2,42 m E (from structure centre)
Target	Ref. RTD section 4.1.
Depth reference	All depths from RT (Rotary Table) unless otherwise stated.
Drilling network	944509
Drilling WBS	L.O046V.002.2A01B01

Outlook

Outlook

ChatGPT/GPT-4 have many use cases.


Best practices are not yet known.

What we believe so far:

- GPT is great for "last mile" interpretation and can smooth over complexity.
- GPT works best with context if accuracy and citing sources are crucial.
- GPT cannot be used "at scale" - must narrow your focus first.
- GPT-4 cannot be retrained on your data, and probably doesn't need to be.
- Open source LLMs are becoming available, but with varying quality.

Over the next ~6 months, we expect to identify and build the most useful and trustworthy applications of this tech.

Contributors to this Research

- SPE Volunteers 
- John Boden, SPE
- Jerrod Quintana, SPE
- Alison Small, SEG
- Reid Smith, i2k Connect
- Madison Gipson, i2k Connect
- Julia Elliott, i2k Connect
- Dalton Hough, i2k Connect
- Eric Schoen, i2k Connect



I2k Connect Inc.

Our i2k Connect AI Platform supports the Research Portal at <https://search.spe.org>

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