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Thank you!



In this module, you learn to ...

- Leverage foundation models for generative Al
- Use Google's foundation models to optimize generative AI tasks
- O3 Start prompting with Vertex AI Studio
- Explore use cases for generative Al
- Find and implement models using Vertex Al Model Garden



Topics

The Benefits of Foundation Models
Google's Foundation Models
Vertex Al Studio
Generative Al Use Cases



This revolution started at Google

Transformers

- Pathbreaking Neural Network Architecture
- Open Sourced by Google in 2017
- Started the revolution in Language Models

T5

(Text-to-Text Transfer Transformer)

- Large Language
 Encoder-Decoder Model
- 10-billion parameter model
- Open Sourced by Google in 2019

Diffusion Models

High Fidelity Image Generation Using Diffusion Models

PaLM

- (Pathways Language Model)
- Single model to generalize across domains
- 540-billion parameter, dense decoder model

Bard

 A conversational Al service powered by LaMDA.

2017

2018

2019

2020

2121

2022

2023

BERT

(Bidirectional Encoder Representations from Transformers)

- World's first Language Model
- Open Sourced by Google in 2018
- SOTA on number of language benchmarks

LaMDA

(Language Model for Dialog Applications)

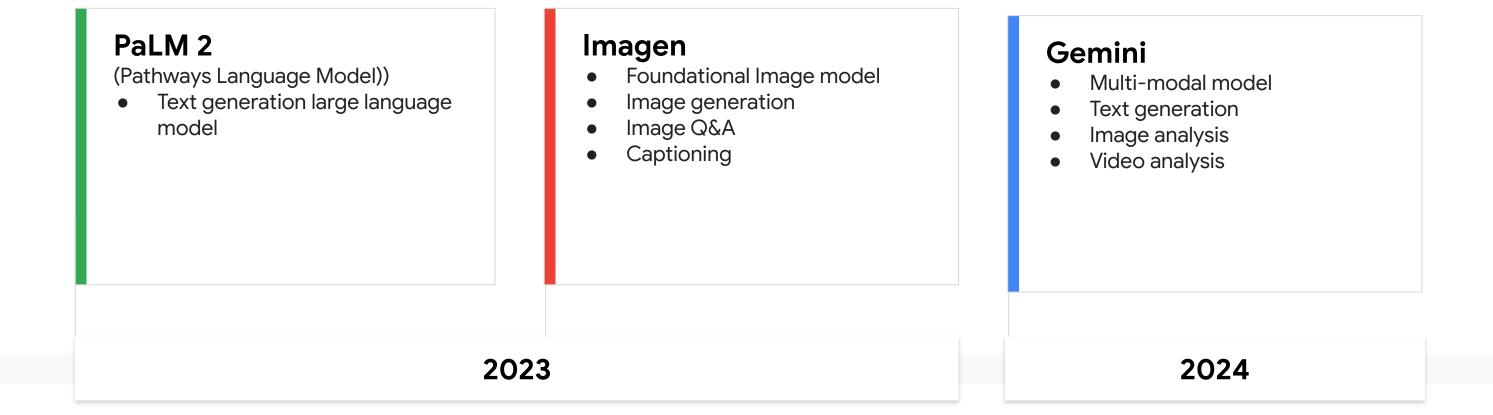
- Model trained on dialogue data
- Model could talk about virtually anything
- Published by Google in 2020

CALM

(Confident Adaptive Language Modeling)

 Accelerating the text generation of LMs

This revolution continues...



Large Language Models (LLMs)

ML algorithms that can **recognize**, **predict**, **and generate** human languages



Pre-trained on petabyte scale text-based datasets resulting in large models with **10s to 100s of billions of parameters**



LLMs are normally pre-trained on a large corpus of text followed by fine-tuning on a specific task



LLMs can also be called **Large Models** (includes all types of data modality) and **Generative AI** (a model that produces content)

Go read this huuuuuuge pile of books.







So, you've learned about cats and millions of other concepts ... what's a cat?

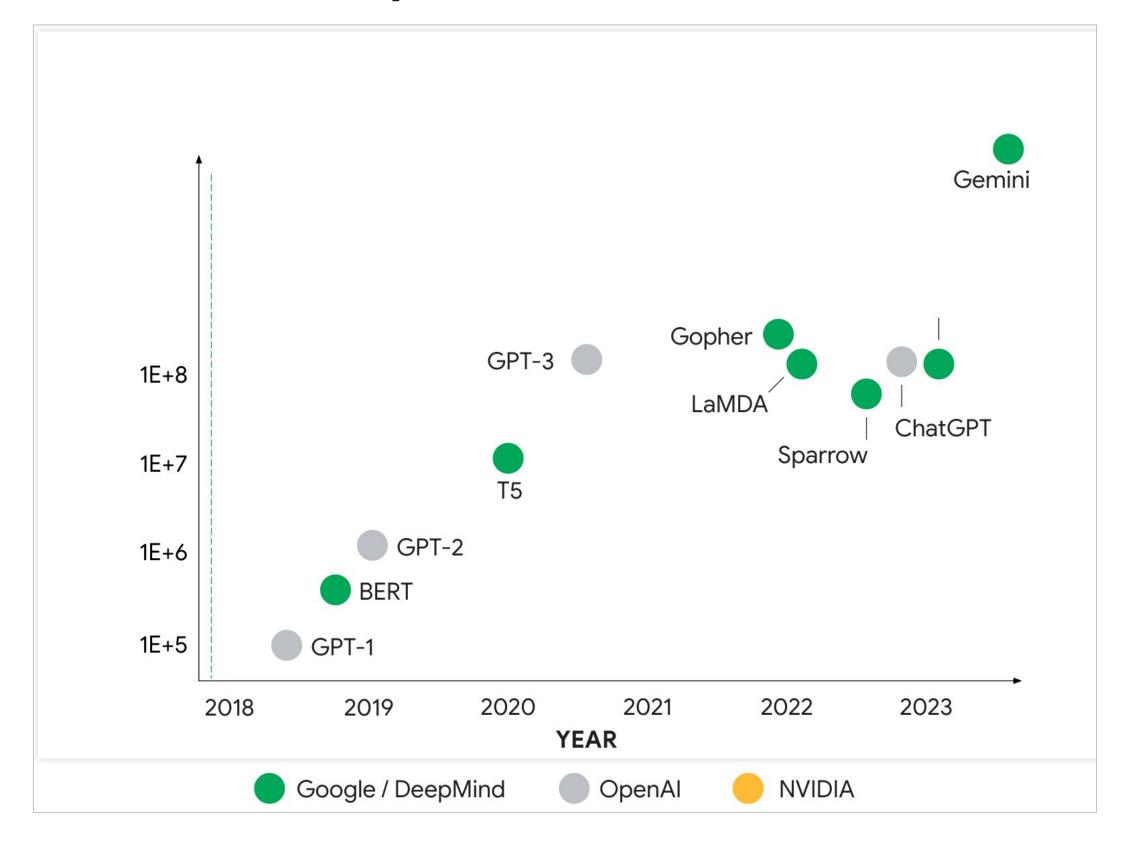


A cat is a small, domesticated carnivorous mammal.

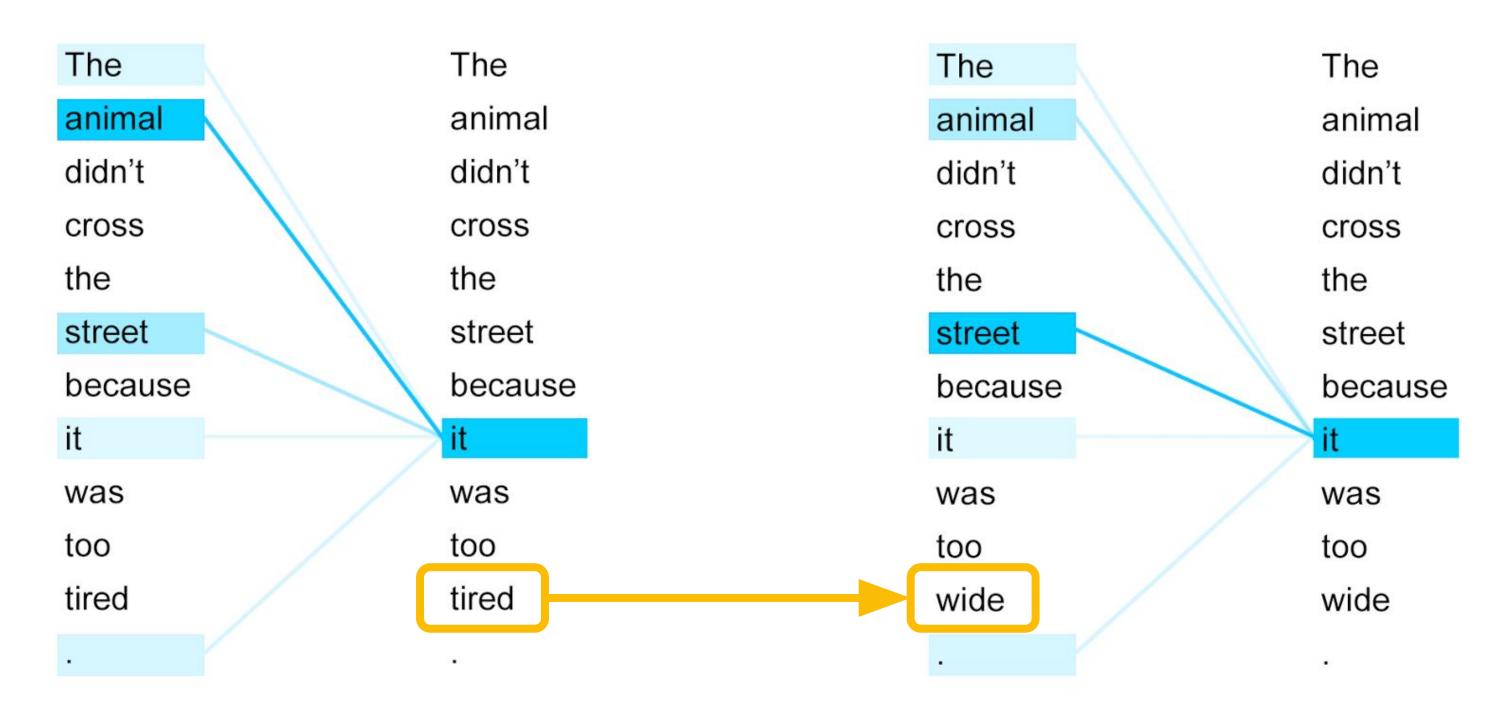


LaMDA, PaLM, GPT-3, etc.

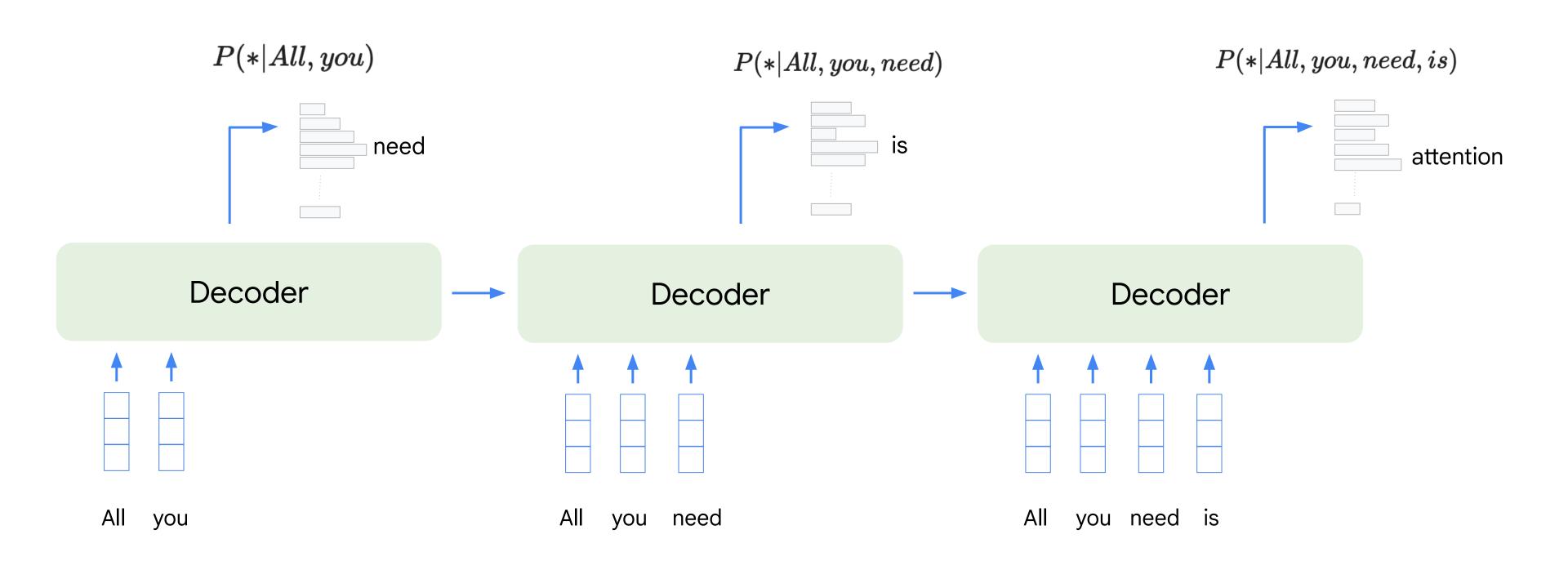
LLMs have driven an explosion in model size



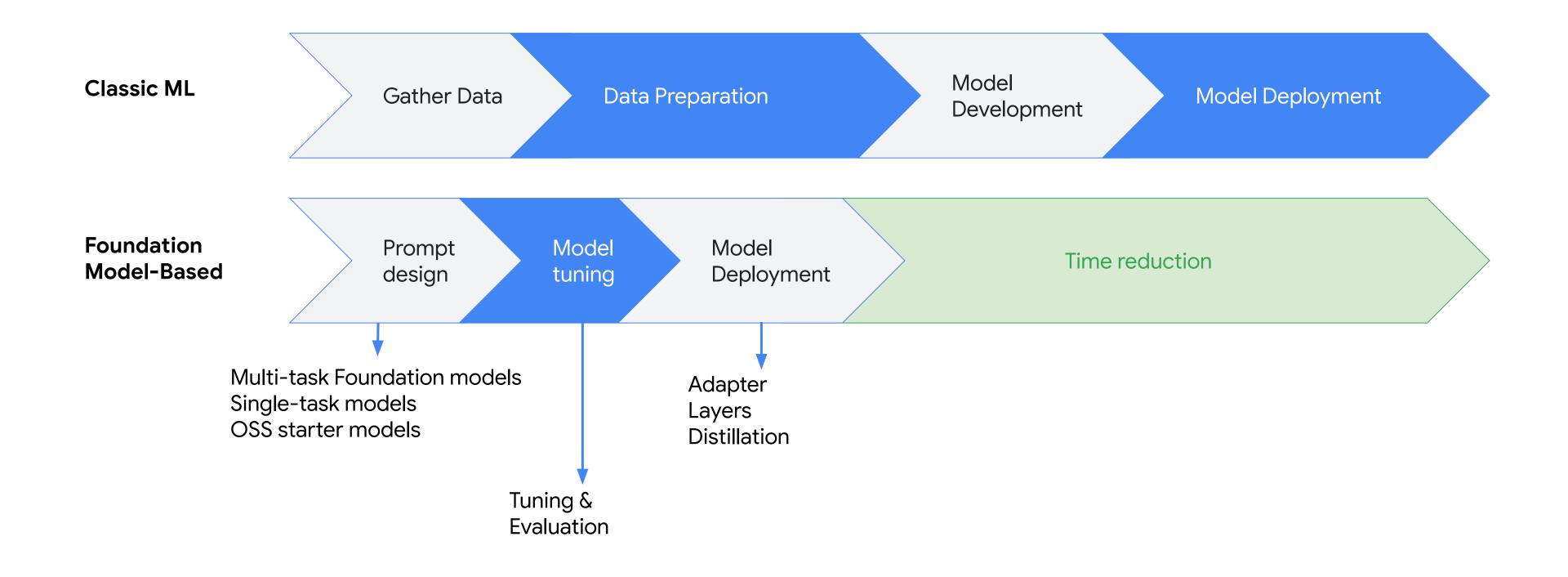
Transformers use a self-attention layer. Enhacing each token's sensitivity to its relationship with other tokens.



The LLM's decoder returns a probability distribution.



Foundational models accelerate time to model deployment



There are also challenges with generative Al

- Ensuring the quality of generated content
- Hallucinations
 - Incorrect statements can be presented in a confident manner
- Preventing offensive or harmful responses



Use cases that build on the strengths of generative Al

Language

- Draft Writing
- Summarization
- Ideation
- Classification
- Sentiment analysis
- Extraction
- Chat
- Search

Code

- Code generation
- Code completion
- Code chat
- Code conversion

Speech

- Speech to text
- Text to speech

Vision

- Image Q&A
- Image generation
- Image editing
- Captioning
- Image search
- Video descriptions

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Gemini is a multimodal foundation model trained on text, images, video and audio

- Prompts can contain a combination of text, images, and video
- Capable of performing a wide range of text and vision-related tasks
 - Generate text
 - Extract text from images and video
 - Caption images, video, or audio
 - Understand and respond to questions about video, text and audio
- Multiple versions:
 - Pro: Most advanced
 - Flash: Nearly as good and faster and cheaper



Gemini's multimodal capabilities mean it can understand images, graphics & tables

Prompt

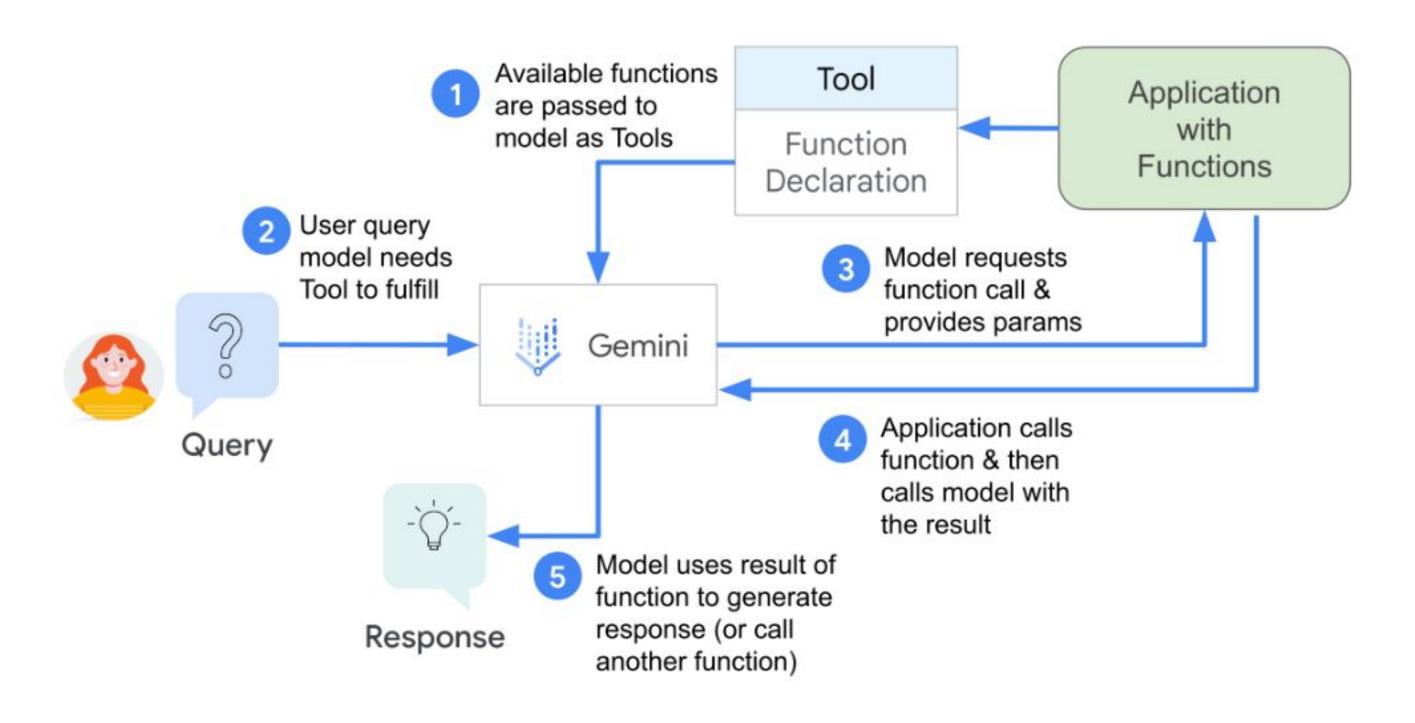


What major event is represented in the image? Which state did it have a severe impact on and when did it make landfall? Answer all questions in bullet points with just the answer, do not use complete sentences.

Response

- Hurricane Ida
- Louisiana
- August 29, 2021

Function Calling lets Gemini pass your system a request for a function to be called, then use the result you return







Application Lifecycle

Efficiently manage cloud applications

Gemini **Cloud Assist**



Software Development

Accelerate software delivery

Gemini Code Assist

Security

Elevate security expertise

Gemini in Security

Data Analytics

Fast-track data analysis

Gemini in BigQuery



Business Intelligence

Automate data Insights

Gemini in Looker

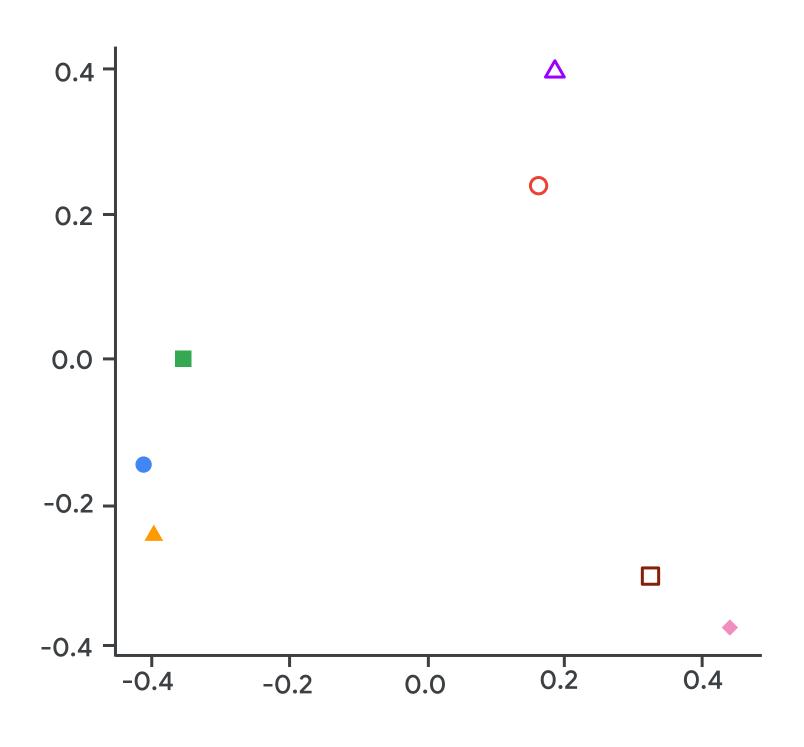


Supercharge database development & management

Gemini in Databases



The Embeddings API returns embeddings for text, text-multilingual or multimodal prompts



sentences

- Missing flamingo discovered at swimming pool
- Sea otter potted on surfboard by beach
- Baby panda enjoys boat ride
- Breakfast themed food truck beloved by all!
- ∧ New curry restaurant aims to please!
- Python developers are wonderful people
- TypeScript, C++ or Java? All are great!

Gemma is a family of lightweight, open models built from the same technology used to create the Gemini

- Small enough to run on mobile devices, desktop and laptop computers, and your own servers
- Comes in multiple flavors
 - Gemma 2: The latest text-only version
 - PaliGemma: Image + text as input, text as output
 - CodeGemma: Further trained on code & math
 - RecurrentGemma: A distinct model focusing on memory efficiency
- Can deploy using Vertex AI Model Registry and Model Endpoints



You can try out Gemma on your own computer

- Go to https://ollama.com/ and download and install the program
- Go to your terminal and type:
 ollama run gemma
- Enter a prompt to try it out



When should you deploy Gemma on a project?

- On systems that can't connect to the Cloud for security or latency reasons
- On edge devices
- For experimenting with whole foundation-model tuning



Imagen is Google's Foundation model for Vision

- Imagen is capable of performing a wide range of vision-related tasks
 - Generate an image
 - Edit a masked section of an image
 - Caption an image
 - Visual Q&A (Answer questions about an image)
 - The documentation shows a <u>feature roadmap</u> with more features planned

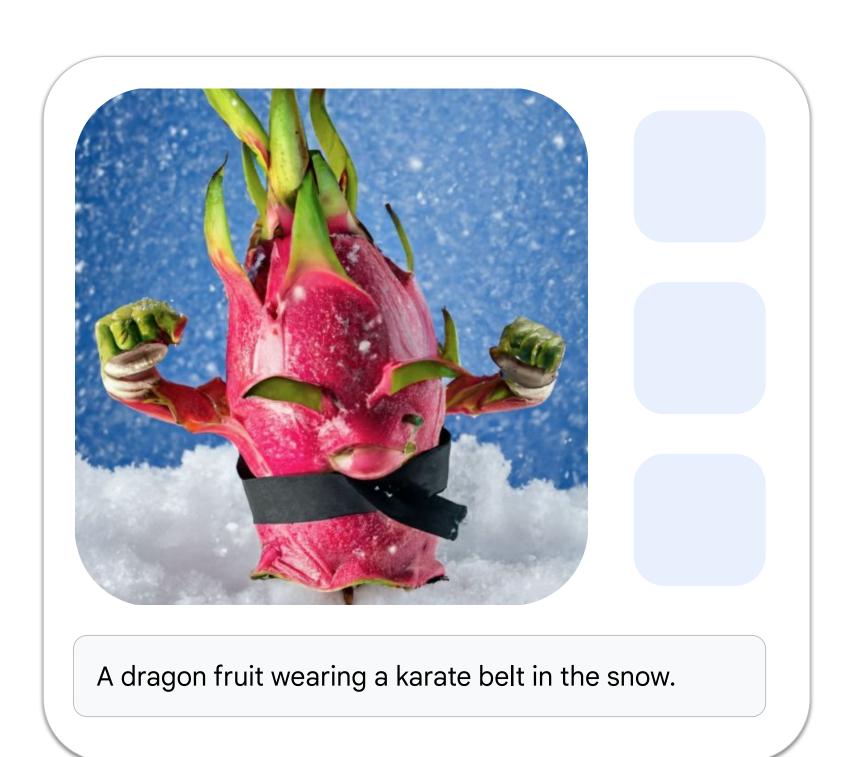
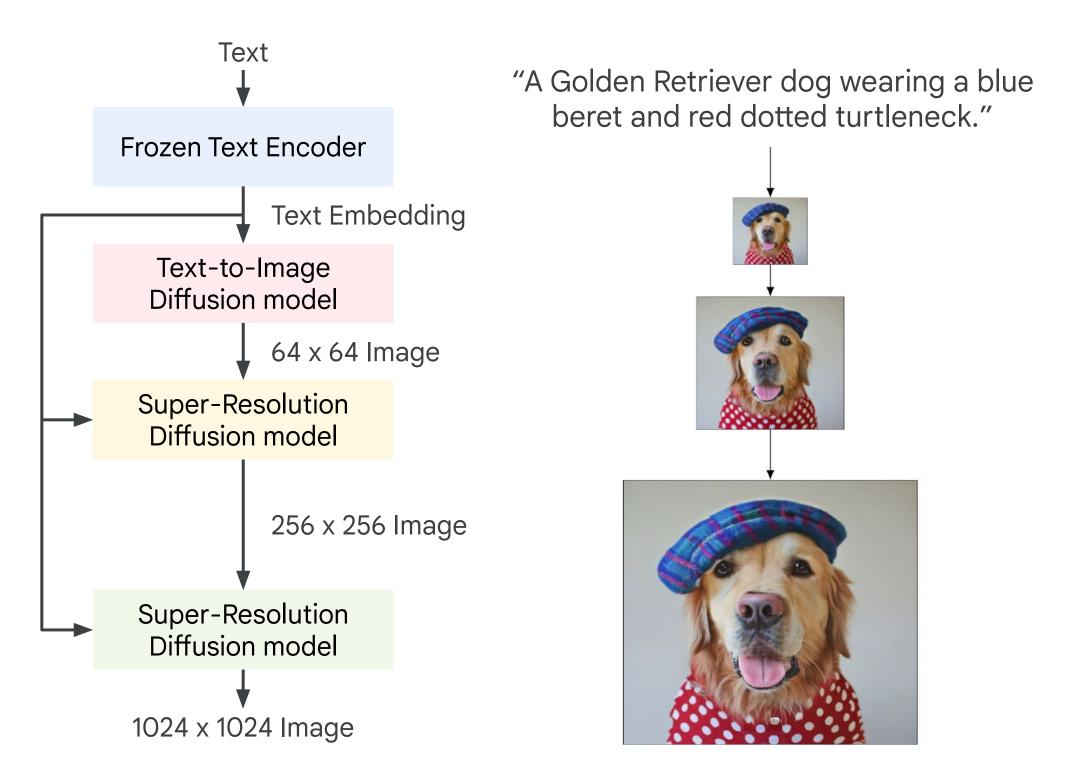
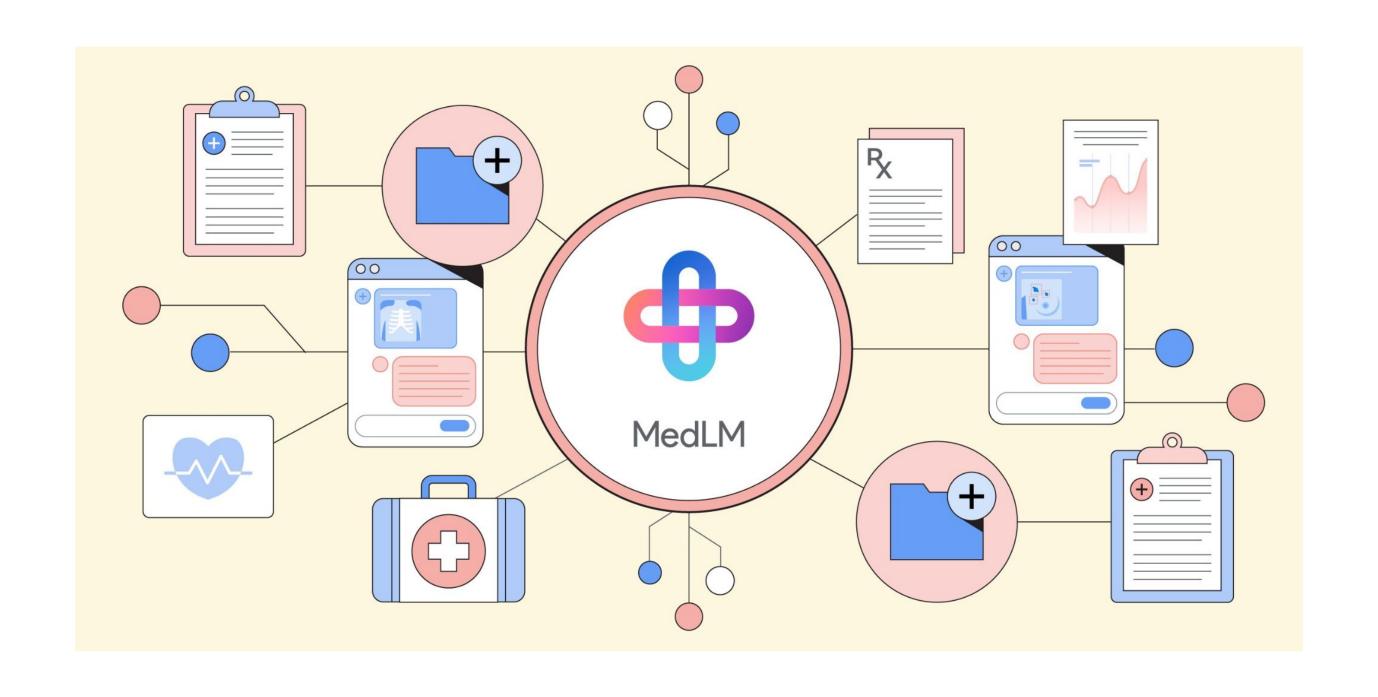


Imagen uses diffusion-based techniques to generate images



Diffusion models iteratively refine a noise-filled image to approximate the target image distribution.

MedLM is a HIPAA-compliant suite of medically tuned models and APIs powered by Google Research



To use Vertex Al models in a web or mobile app, investigate using Firebase GenKit

- Designed for app developers to integrate generative AI models into Firebase web or mobile applications
- Currently supports JavaScript/Typescript (Node.js)
 with Go support in active development

```
import { gemini15Flash } from '@genkit-ai/vertexai';
import { generate } from '@genkit-ai/ai';

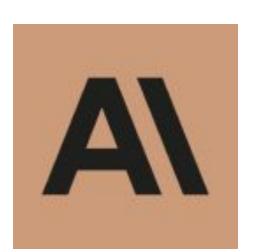
const result = await generate({
  model: gemini15Flash,
  config: { temperature: 0.3, maxOutputTokens: 200 },
  prompt: 'What makes you the best LLM out there?',
});
console.log(result.text());
```



Firebase Genkit

And other models are available in Model Garden to run on Google Cloud!









You can call Anthropic's Claude natively on Vertex Alusing its API or through LangChain

```
from anthropic import AnthropicVertex
client = AnthropicVertex(region="us-east5", project_id=PROJECT_ID)
message = client.messages.create(
   max_tokens=1024,
   messages=[
           "role": "user",
           "content": "Send me a recipe for banana bread.",
   model="claude-3-5-sonnet@20240620")
print(message.model_dump_json(indent=2))
```

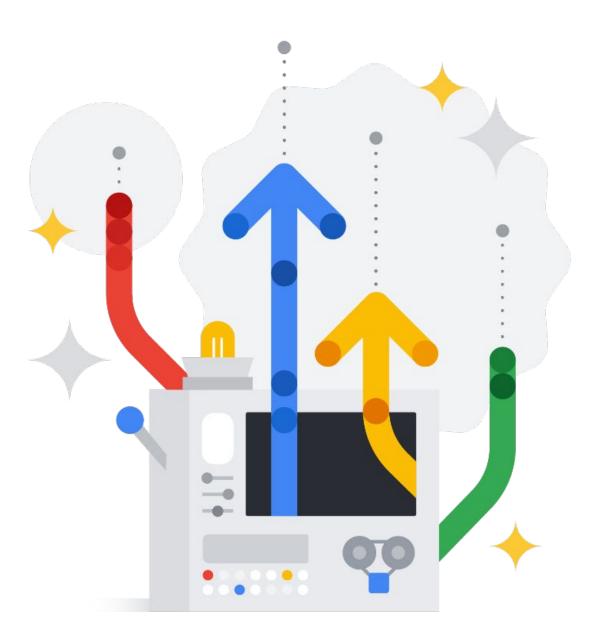
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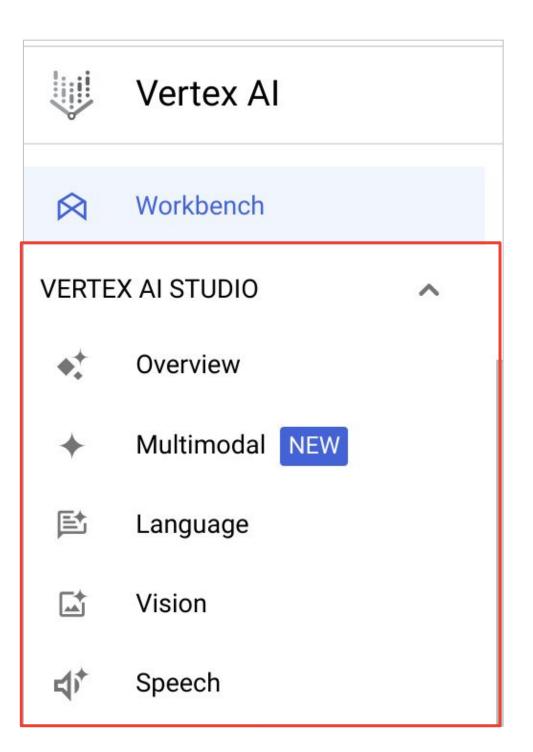
Vertex Al Studio with Google foundation models

- Supports Google foundational models
 - Gemini Pro and Flash for text and code generation
 - Gemini Pro Vision for Image and Video Q&A
 - PaLM 2 models for text and chat
 - Chirp for speech to text
 - Imagen for text to image generation
- Allows users to easily experiment with prompts
 - Simple, intuitive design
 - Easily experiment with parameters
 - Add context and examples

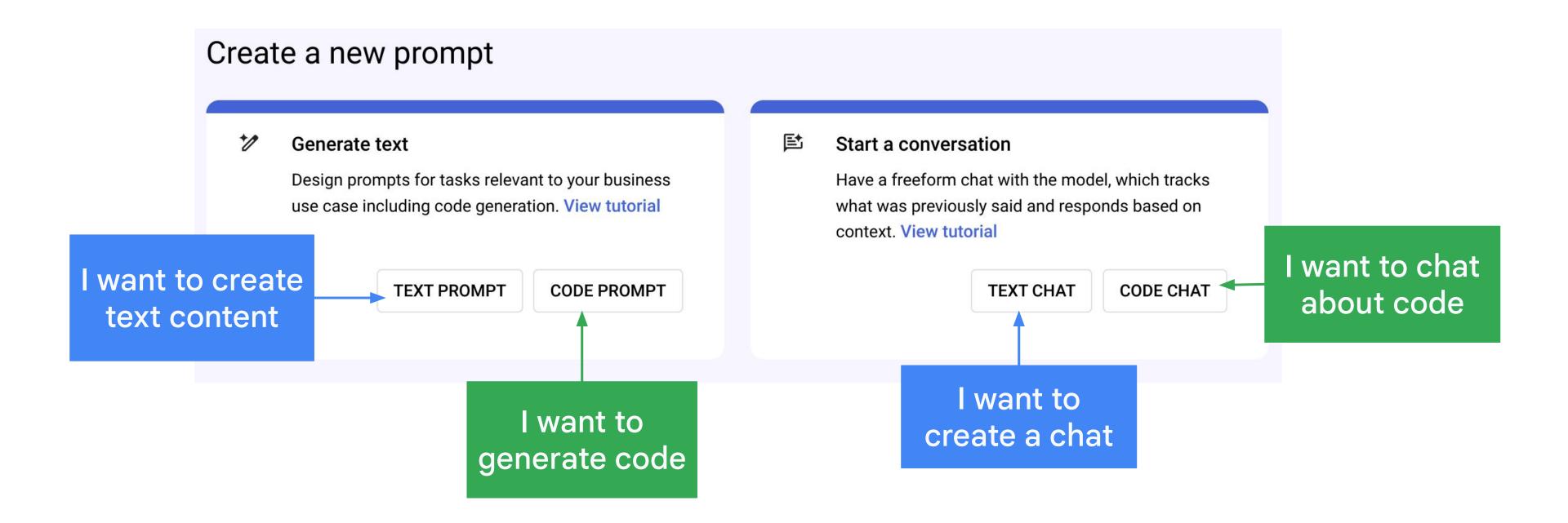


Vertex Al Studio

- Vertex AI Studio is available as a feature of Google Cloud Vertex AI
- Choose from Multimodal, Language, Vision, or Speech models

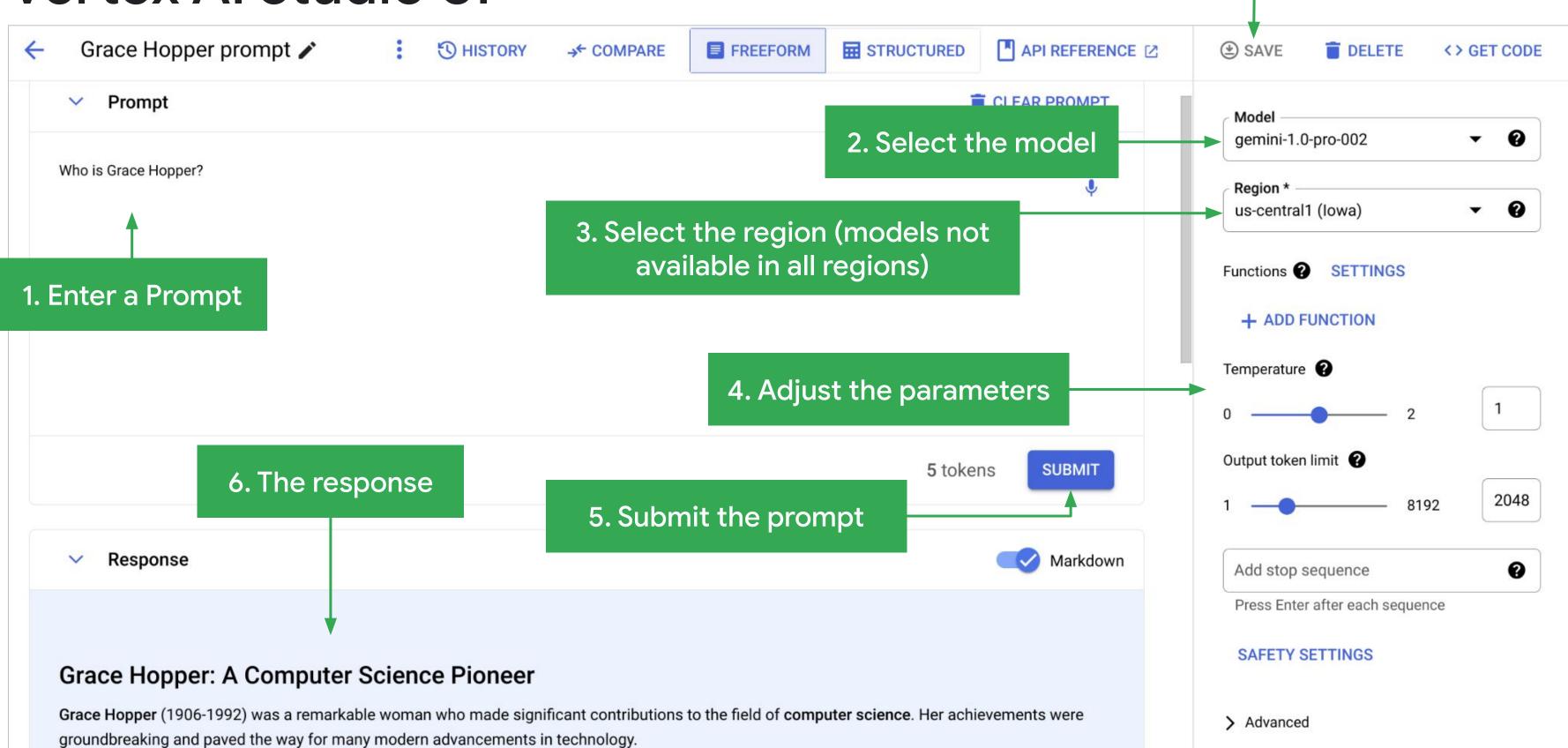


To get started, choose a task based on your goal

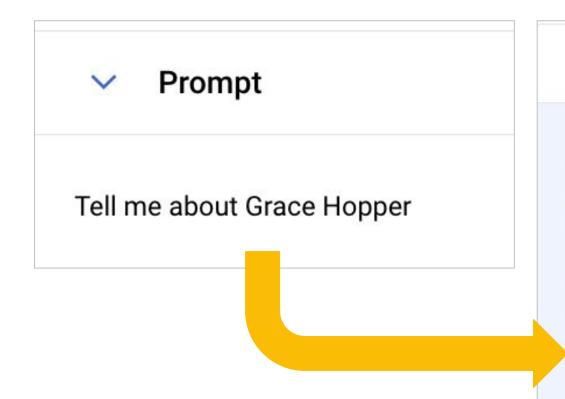


7. Save the model

Vertex Al Studio Ul



Test a simple text prompt to see the results







Grace Hopper was an American computer scientist and United States Navy rear admiral. She was one of the pioneers of computer programming, and is credited with coining the term "debugging". She also helped develop the first compiler, which translates human-readable code into machine code that computers can understand.

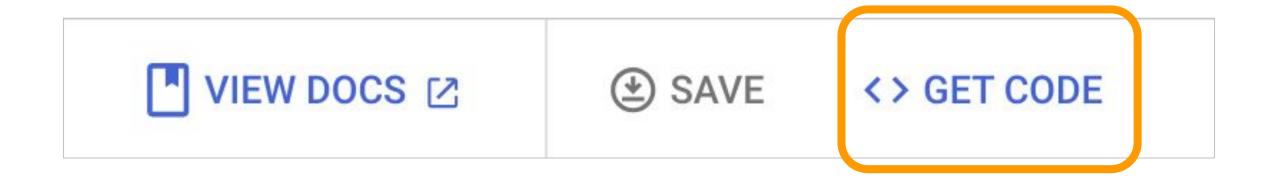
Hopper was born in New York City in 1906. She attended Vassar College, where she studied mathematics and physics. After graduating, she taught mathematics at Vassar for a year before joining the United States Navy in 1943.

During World War II, Hopper worked on the Mark I computer, one of the first electronic computers. She was responsible for developing the first compiler, which translated human-readable code into machine code that computers could understand. This work made it much easier for programmers to write code for computers, and helped to make computers more accessible to a wider range of people.

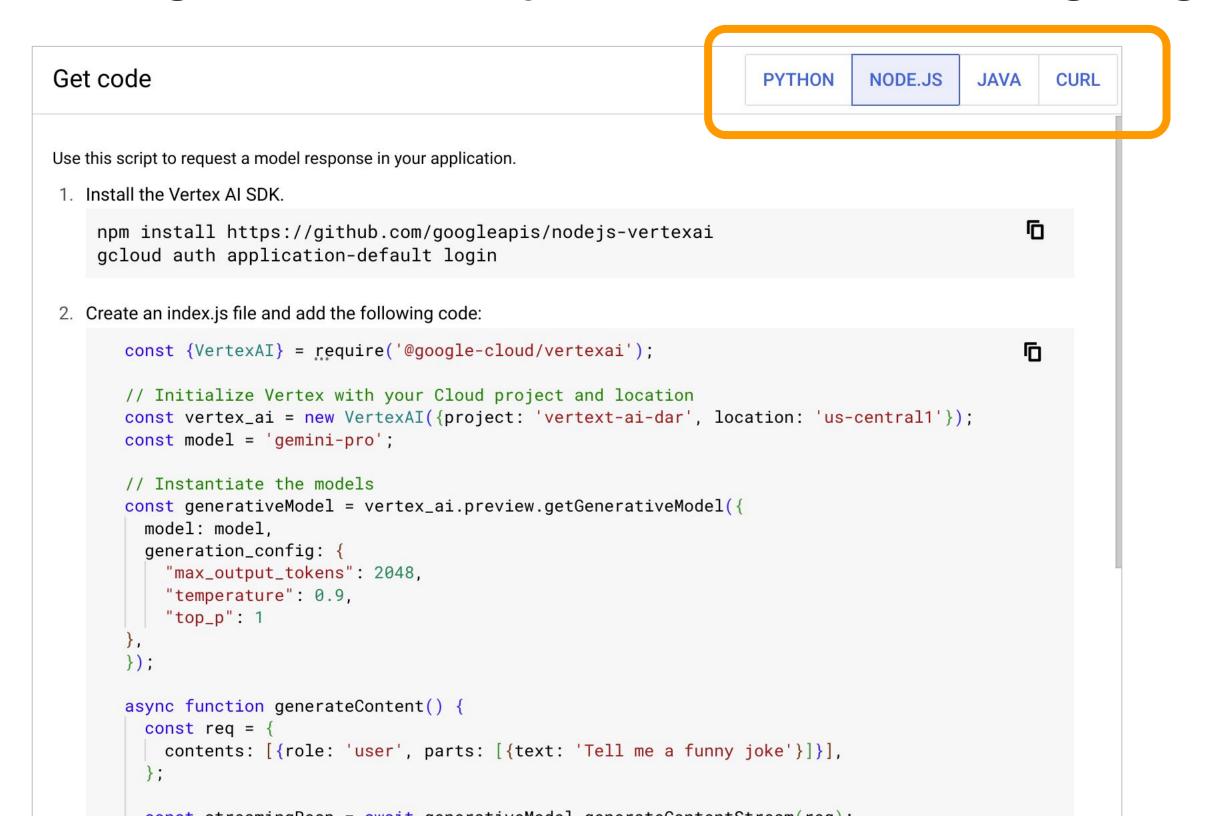
After the war, Hopper continued her work in computer science. She helped develop the COBOL programming language, which is still widely used today. She also served as the director of the Navy's computer science research center.

In 1986, Hopper was awarded the National Medal of Technology for her contributions to computer science

Use < > Get Code from Vertex Al Studio to provide template code



Get package installation and code with any parameters or safety settings you've adjusted in a few languages



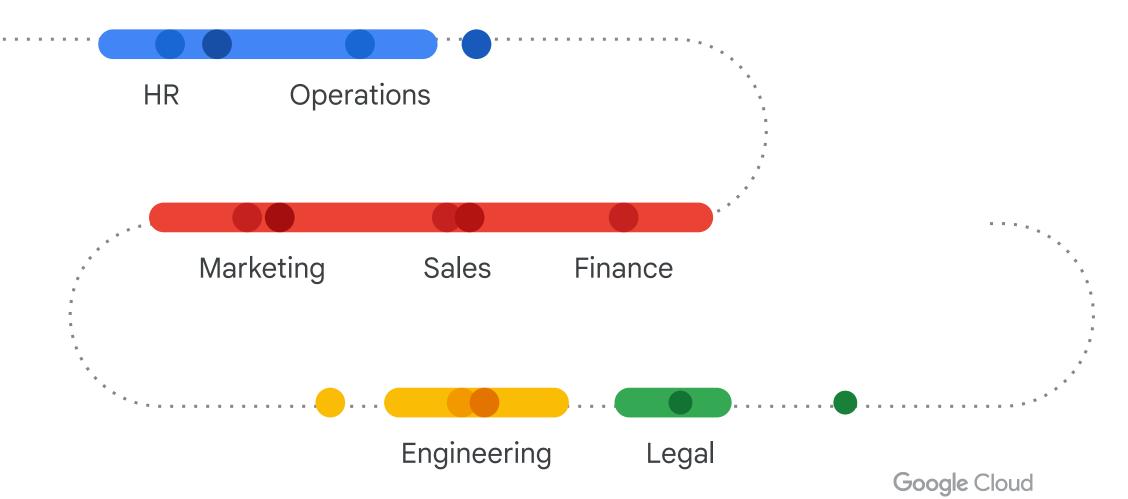
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Generative Al Market Opportunities



There are many opportunities for Generative Al across many organizations

- Content creation
- Marketing and advertising
- Customer service
- Education and research
- Many more...



1: Software development

Expedite the coding process by providing developers with the ability to generate, troubleshoot, and conduct unit testing for their code base

\$11.9M - 23.8M¹

in potential cost savings opportunities

- + Decrease time spent writing and troubleshooting code
- + Simplify code documentation process
- + Automate unit test case development

| | 6,349 | Number of developers |
|---------------|---------------|--|
| | \$150,000 | Salary per developer |
| | \$952,350,000 | Salary paid to developers |
| 20.0% | 10.0% | Percentage increase in developer productivity |
| \$190,470,000 | \$95,235,000 | Potential reduction in developer cost from improved productivity |
| | 50.0% | % of developers usage |
| | 25.0% | Percentage of value realize |
| Top-end | Conservative | |
| \$23,808,750 | \$11,904,375 | Estimated annual cost savings with software development GenAl |

2: Media content search

Reduce subscriber churn from improved user search experience (e.g., ability to find more relevant content)

 $$32M - 65M^{1}$

in potential revenue improvement opportunities

+ Recapture of revenue that would have been lost from customer churn due to lack of relevant content

Value calculation (annualized)

| Number of subscribers | 238,390,000 | |
|--|--------------|--------------|
| Subscriber churn rate (%) | 2.40% | |
| Number of churned subscribers | 5,721,360 | |
| Potential decrease in subscriber churn from better search experience | 5.0% | 10.0% |
| Number of subscribers saved | 286,068 | 572,136 |
| Average subscription cost per user per month | \$12 | |
| Revenue from saved subscribers | \$40,392,843 | \$80,785,686 |
| EBITDA margin (%) | 80.0% | |
| | Conservative | Top-end |
| Estimated annual profits from subscribers saved | \$32,314,274 | \$64,628,549 |
| | | |

Google Cloud

2: Media content search

Increase advertisement inventory from growth in watch time due to improved user search experience

 $$36M - 71M^{1}$

in potential revenue improvement opportunities

+ Increase in ads revenue by increasing average watch time for ad-supported subscribers

| Number of subscribers | 238,390,000 | |
|--|---------------|--------------|
| Percentage of subscribers using ad-supported tier (%) | 2.00% | |
| Number of subscribers using ad-supported tier | 4,767,800 | |
| Average hours of watch time per week | 22 | |
| Number of hours of watch time | 5,553,533,440 | |
| Potential increase in watch time | 2.5% | 5.0% |
| Hours increase in watch time due to better search experience | 138,838,336 | 277,676,672 |
| Number of ads per hour of watch time | 8 | |
| Average CPM (per 1,000 impressions) (\$) | \$40.00 | |
| Revenue from incremental ads due to more watch time | \$44,428,268 | \$88,856,535 |
| EBITDA margin (%) | 80.0% | |
| | Conservative | Top-end |
| Esimated annual profits from more ads | \$35,542,614 | \$71,085,228 |
| | | |

3: Retail customer experience

Decrease live chat cost with chat containment

 $$4.4M - 17.5M^{1}$

in potential cost consolidation opportunities

+ Enable customers with simple questions to get them answered without having to wait and engage directly with a live service agent

| Annual website chat session | 73,000,000 | |
|---|----------------|-----------------|
| Current chat containment % | 25.00% | |
| Number of live chat sessions | 54,750,000 | |
| Potential increase in chat containment | 5.0% | 20.0% |
| Number of additional live chat sessions contained | 2,737,500 | 10,950,000 |
| Cost per live chat | \$1.60 | |
| | Conservative | Top-end |
| Estimated cost savings from containment | \$4,380,000.00 | \$17,520,000.00 |

3: Retail customer experience

Increase contact center agent and store employee productivity and improve customer experience with LLM-powered assistance

 $$28M - 55M^{1}$

in potential cost consolidation opportunities

+ Improve productivity of customer-facing staff, allowing them to dedicate more hours in the day to help and support end-customers

Value calculation (annualized)

| Number of contact center agents 5,000 Number of store representatives 50,000 Average salary per contact center agents and store representatives Salary paid to contact center agents and store representatives Percentage increase in productivity 5.0% 10.0% Potential cost savings with increased productivity Percentage value realize 25.00% Conservative Top-end Estimated cost savings from productivity increase \$27,500,000 \$55,000,000 | | | |
|---|-------------------------------------|-----------------|---------------|
| Average salary per contact center agents and store representatives Salary paid to contact center agents and store representatives Percentage increase in productivity Potential cost savings with increased productivity Percentage value realize Conservative Top-end Estimated cost savings from \$27,500,000 \$40,000 \$2,200,000 \$2,200,000,000 \$220,000,000 \$220,000,000 \$255,000,000 | Number of contact center agents | 5,000 | |
| agents and store representatives Salary paid to contact center agents and store representatives Percentage increase in productivity Potential cost savings with increased productivity Percentage value realize S2,200,000,000 \$10.0% \$110,000,000 \$220,000,000 \$220,000,000 Conservative Top-end Estimated cost savings from \$27,500,000 \$55,000,000 | Number of store representatives | 50,000 | |
| and store representatives Percentage increase in productivity Potential cost savings with increased productivity Percentage value realize \$2,200,000,000 \$10.0% \$110,000,000 \$220,000,000 \$220,000,000 \$220,000,000 \$25.000 \$25.000,000 \$55.000,000 | , , | \$40,000 | |
| Potential cost savings with increased productivity Percentage value realize 25.00% Conservative Top-end Estimated cost savings from \$27,500,000 \$55,000,000 | , , | \$2,200,000,000 | |
| productivity Percentage value realize 25.00% Conservative Top-end Estimated cost savings from \$27,500,000 \$220,000,000 \$220,000,000 \$220,000,000 \$25,000,000 | Percentage increase in productivity | 5.0% | 10.0% |
| Conservative Top-end Estimated cost savings from \$27,500,000 \$55,000,000 | - | \$110,000,000 | \$220,000,000 |
| Estimated cost savings from \$27,500,000 \$55,000,000 | Percentage value realize | 25.00% | |
| \$27.500.000 \$55.000.000 | | Conservative | Top-end |
| | u | \$27,500,000 | \$55,000,000 |

Google Cloud

3: Retail customer experience

Drive incremental sales with better customer service by agents (e.g., better knowledge, faster response) that improve customer experiences

\$7.3M - 25.5M¹

in potential revenue improvement opportunities

+ Enable customer service agents to be more informed and better equipped to answer product questions, increasing the speed and likelihood of sales

| Annual company revenue (\$) | \$45,000,000,000 | |
|---|------------------|---------------|
| Percentage of sales with customer service agents engagement | 16.20% | |
| Annual company revenue impacted by customer service agents | \$7,290,000,000 | |
| Potential increase in revenue impacted by customer service agents | 2.0% | 7.0% |
| Estimated revenue increase | \$145,800,000 | \$510,300,000 |
| EBITDA margin (%) | 5.0% | |
| | Conservative | Top-end |
| Estimated annual profits from better | ¢7200 000 | ¢25 515 000 |
| customer service by agents | \$7,290,000 | \$25,515,000 |

4: Health Insurance Customer Service

Improve customer experience and provide relief for customer service centers by introducing a responsive patient service

 $$21M - 63.2M^{1}$

in potential financial impact

- + Decrease 10-30% live agent calls from containment²
- + Increase contact center agent productivity by 10-30%²
- + Revenue recapture from improved call abandonment by 10-30%²

| 15,000,000 | Number of inbound calls, annually |
|------------|--|
| 10% | Current call containment rate (%) |
| \$10.00 | Cost per call |
| 5,000 | Number of contact center agent |
| \$30,000 | Annual salary per CC agent |
| 5% | % of inbound calls attempt to make payment |
| 20% | Current call abandonment rate (%) |
| \$50 | Revenue capture per call |
| 10% | EBITDA margin |

4: Health Insurance Customer Service

Improve customer experience and provide relief for customer service centers by introducing a responsive patient service

\$7.5M - 22.5M¹

in potential cost savings opportunities

- + Increase contact center agent productivity by 10-30%²
- + Decrease 10-30% live agent calls from containment²
- + Revenue recapture from improved call abandonment by 10-30%²

| Number of contact center agents | 5,000 | |
|---|---------------|--------------|
| Salary per contact center agent | \$30,000 | |
| Salary paid to contact center agents | \$150,000,000 | |
| Percentage increase in agent productivity | 10.0% | 30.0% |
| Potential reduction in developer cost from improved productivity | \$15,000,000 | \$45,000,000 |
| Percentage of value realize | 50.0% | |
| | Conservative | Top-end |
| Estimated annual cost savings with agent productivity improvement | \$7,500,000 | \$22,500,000 |

4: Health Insurance Customer Service

Decrease live call cost with call containment

 $$13.5 - 40.5M^{1}$

in potential cost consolidation opportunities

- + Decrease 10-30% live agent calls from containment²
- + Increase contact center agent productivity by 10-30%²
- + Revenue recapture from improved call abandonment by 10-30%²

| Number of inbound calls, annually | 15,000,000 | |
|---|--------------|--------------|
| Current chat containment % | 10.00% | |
| Number of live calls | 13,500,000 | |
| Potential increase in chat containment | 10.0% | 30.0% |
| Number of additional live chat sessions contained | 1,350,000 | 4,050,000 |
| Cost per live chat | \$10 | |
| | Conservative | Top-end |
| Estimated cost savings from containment | \$13,500,000 | \$40,500,000 |

5: Automotive conversational manual and assistant

Provide conversational manual and assistant to assist drivers in automotive vehicles

 $$5.8M - 17.6M^{1}$

in potential financial impact

- + Decrease 10-30% live agent calls from containment²
- + Increase revenue and upsell car features and services by 5-15%

| 5,000,000 | Number of inbound calls from conversation manual, annually |
|-----------|---|
| \$8.00 | Cost per call |
| \$150B | Annual revenue |
| 2.5% | Percentage of revenue from car services and features |
| 10% | % of car services and features revenue from conversation manual |
| 10% | EBITDA margin |

6: Financial Services Analyst Research

Improve financial services research analyst productivity by enabling them to query bodies of financial data and reports in natural language

\$400 - 700k¹

in potential cost consolidation opportunities

- + Drive Financial Research Analyst productivity by decreasing time spent searching for information
- + Improve employee satisfaction

| Number of Financial Research Analyst | 250 | |
|--|--------------|-------------|
| Salary per Analyst | \$80,000 | |
| Salary paid to developers | \$20,000,000 | |
| Time spent searching for information ² | 20% | |
| Percentage increase in productivity ³ | 20.0% | 35.0% |
| Potential reduction in analyst cost from improved productivity | \$800,000 | \$1,400,000 |
| Percentage value realization | 50.00% | |
| | Conservative | Top-end |
| Estimated annual cost savings with increased productivity | \$400,000 | \$700,000 |
| | | |

7: Marketing Campaign Planning

Automate and expedite the Marketing campaign planning of briefs, creatives and assets across multi-channel platforms

\$35M-70M+1

in potential cost consolidation opportunities

- Drive marketing campaign creation productivity by decreasing time and money spent on campaign planning, briefs, and asset creation
- + Automate Multi-Channel Campaigns

| Total Annual Revenue | \$50,000,000,000 | |
|--|------------------|--------------|
| % of revenue spent on marketing ¹ | 3.00% | |
| Marketing Spend | \$1,500,000,000 | |
| Marketing Spend (TV Only) % | 42.00% | |
| Marketing Spend excluding TV spend | \$870,000,000 | |
| % Campaign Planning Costs | 20% | |
| Total Campaigning Planning Costs minus 20% for conservative estimates | \$139,200,000 | |
| Potential cost savings ² | 25.0% | 50.0% |
| | Conservative | Top-end |
| Estimated annual cost savings with marketing GenAl | \$34,800,000 | \$69,600,000 |

8: Knowledge Workers Productivity

Assist knowledge workers to search for information and to get answers to questions quicker

\$562M - 788M

in potential financial impact opportunities

- + Increase Knowledge Workers productivity
- + Improve employee experience

Value calculation (annualized)

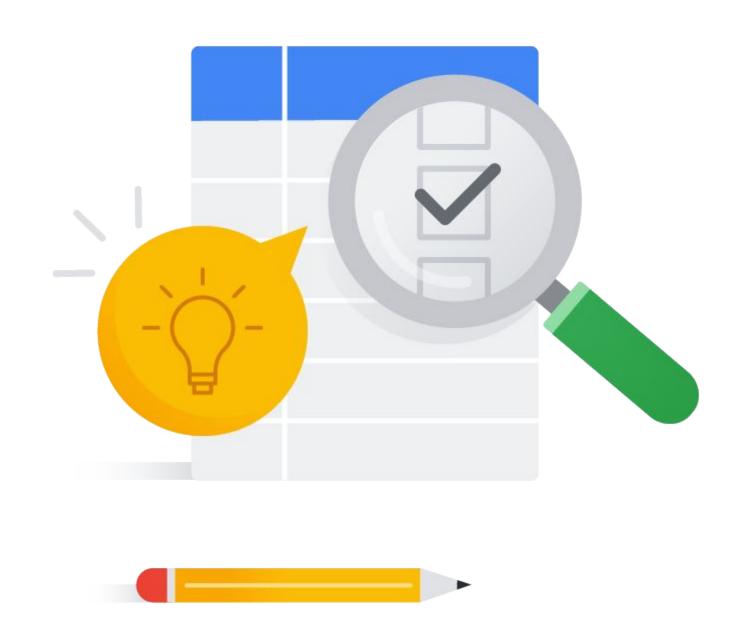
| Number of employees + contract workers | 150,000 | |
|---|------------------|-----------------|
| Percentage of overall employees who are Knowledge workers | 33% | |
| Annual salary per Knowledge Employees | \$80,000 | |
| Annual salary paid to Knowledge Employees | \$12,000,000,000 | |
| Percentage of time searching for information ² | 25% | |
| Percentage of employees GenAl tool usage | 75% | |
| Percentage time reduction searching for information with GenAl tools ^{3,4} | 50.0% | 70.0% |
| Potential reduction in knowledge employees cost from improved productivity | \$1,125,000,000 | \$1,575,000,000 |
| Percentage value realization | 50.00% | |
| | Conservative | Top-end |
| Estimated annual cost savings with Specialized Knowledge Workers | \$562,500,000 | \$787,500,000 |
| | | |

Google Cloud

Lab



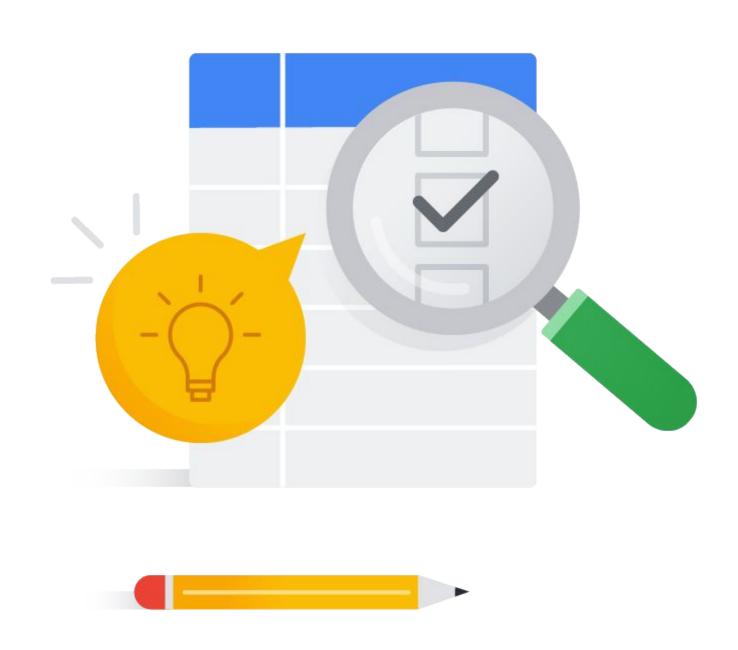
Lab: Multimodality with Gemini



Lab



Lab: Explore and Evaluate Models using Model Garden

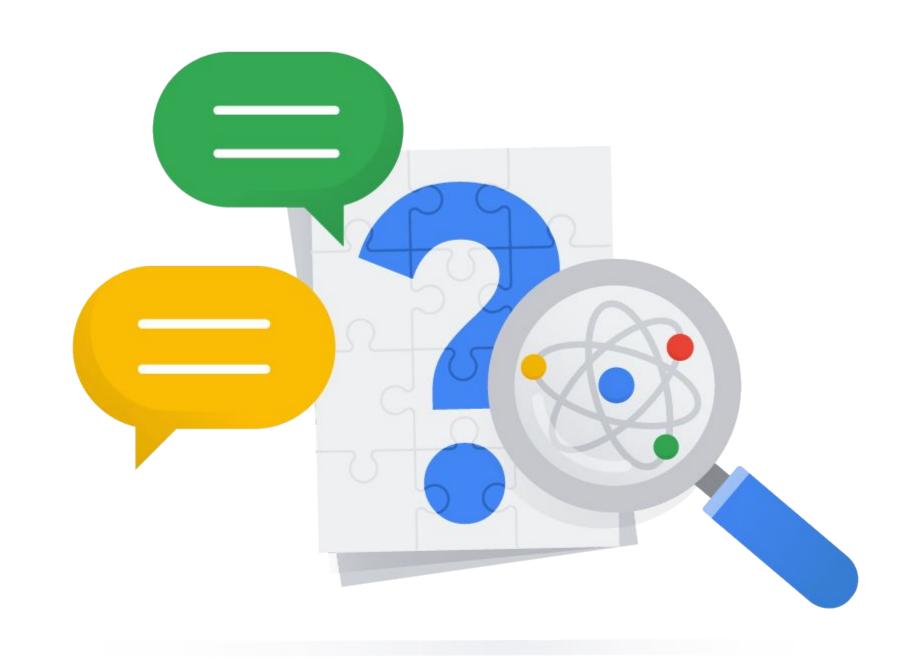


In this module, you learned to ...

- Leverage foundation models for generative Al
- Use Google's foundation models to optimize generative AI tasks
- O3 Start prompting with Vertex AI Studio
- Explore use cases for generative AI
- Find and implement models using Vertex Al Model Garden



Questions and answers



Which of the following are tuned versions of the PaLM model, optimized for specific use cases? (Choose all that apply)

A: Codey

B: Chat-Bison

C: Med PaLM

D: Sec PaLM

E: ChatGPT

F: Imagen

G: Dall-e

Which of the following are tuned versions of the PaLM model, optimized for specific use cases? (Choose all that apply)

A: Codey

B: Chat-Bison

C: Med PaLM

D: Sec PaLM

E: ChatGPT

F: Imagen

G: Dall-e

What tool could you use to find an appropriate ML model based on a use case, and find documentation for a chosen model?

A: AutoML

B: Model Garden

C: Workbench

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A large language model like Google PaLM or GPT could perform which of the following ML tasks? (Choose all that apply)

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B: Summarization

C: Image generation

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E. Sentiment analysis

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