

Generative Al with Google

Getting Started with Generative Al



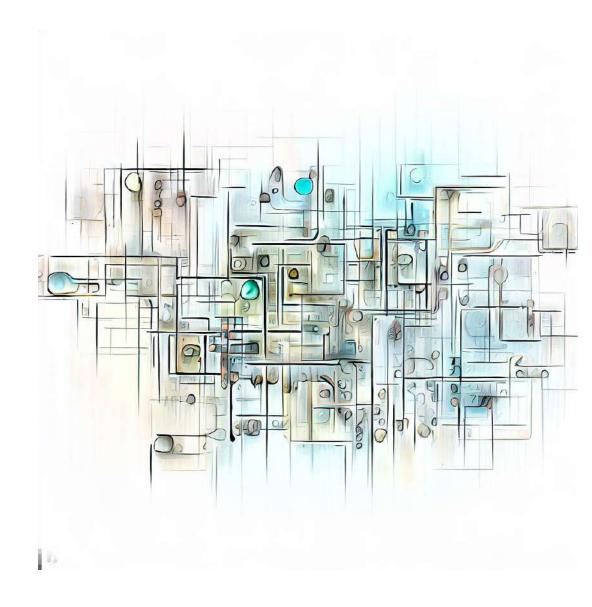
- Artificial Intelligence is in its second golden phase (IMHO):
 - First Phase Early successes in the 1960s and 1970s
 - Second Phase Last two decades or so driven by:
 - New algorithms
 - Massive datasets
 - Powerful computing hardware



Getting Started with Generative AI - 2



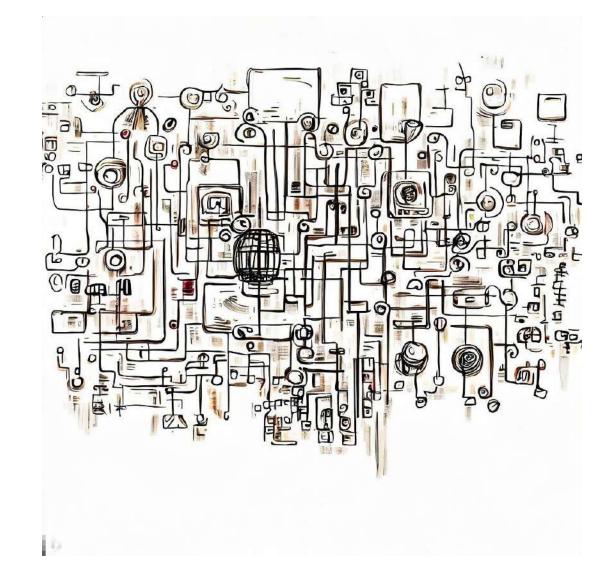
- HOWEVER, building AI solutions has NOT been easy:
 - Scarcity of skills
 - Need to create/manage massive datasets
 - Complex infrastructure needs
 - Complexity of managing AI models



Getting Started with Generative AI - 3



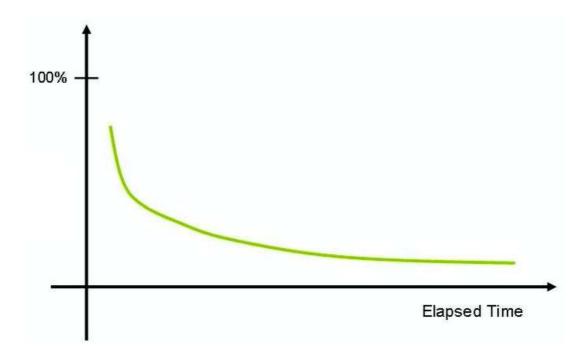
- How can you use Al WITHOUT Al skills/complex infrastructure?
 - Use low-code AI platforms (AutoML)
 - Use pre-trained models (especially Generative AI models)
 - Google offers a plethora of AI solutions around Generative AI:
 - o Bard: Chatbot
 - PaLM API & MakerSuite: Easy to consume APIs
 - Gen. Al Studio (Vertex AI): Google Cloud Service
- Our Goal: Help you understand AI, ML and Generative AI while exploring Generative AI solutions offered by Google



How do you put your best foot forward?



- Learning Gen. Al can be tricky:
 - Lots of new terminology
 - Lots of services
- As time passes, we forget things
- How do you improve your chances of remembering things?
 - Active learning think and make notes
 - Review the presentation once in a while



Our Approach



- Three-pronged approach to reinforce concepts:
 - Presentations (Video)
 - Demos (Video)
 - Two kinds of quizzes:
 - Text quizzes
 - Video quizzes
- (Recommended) Take your time. Do not hesitate to replay videos!
- (Recommended) Have Fun!

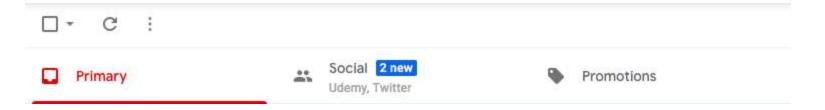




Artificial Intelligence

Artificial Intelligence - All around you





- Self-driving cars
- Spam Filters
- Email Classification
- Fraud Detection

What is AI? (Oxford Dictionary)



The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decisionmaking, and translation between languages

What is AI? (in Simple Terms)

- Goal of AI: Create machines that can simulate human-like intelligence and behavior
 - Play Chess
 - Play Go
 - Make purchase decisions
 - Drive a car
 - Write an essay!



Understanding Types of Al



- Strong artificial intelligence (or general AI): Intelligence of machine = Intelligence of human
 - A machine that can solve problems, learn, and plan for the future
 - An expert at everything
 - Including learning to play all sports and games!
 - Learns like a child, building on it's own experiences
 - We are far away from achieving this!
 - Estimates: few decades to never
- Narrow AI (or weak AI): Focuses on specific task
 - Example: Self-driving car
 - Example: Playing Chess
 - Example: Predicting House Price



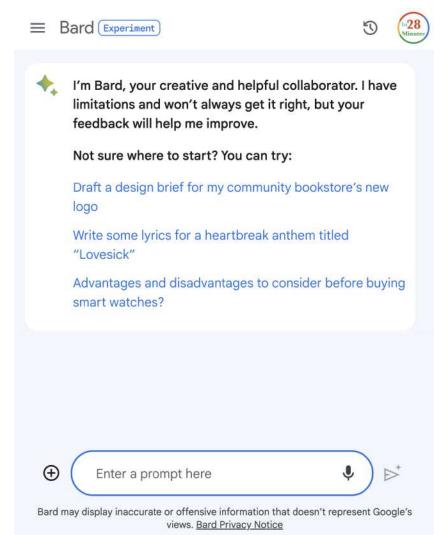
Playing with Bard



- Bard: Google's Generative AI Chatbot!
 - I'm Bard, your creative and helpful collaborator. I have limitations and won't always get it right, but your feedback will help me improve.

A Demo of Bard:

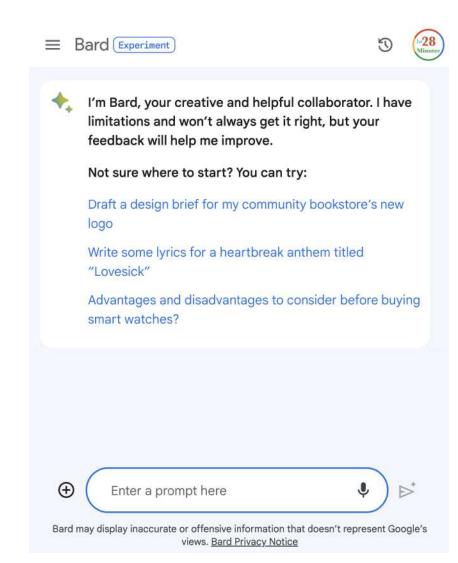
- You are Lex Friedman. You are going to interview Sachin Tendulkar tomorrow. What are the FIRST FIVE questions that you are going to ask?
- Act as Sachin Tendulkar. You are meeting Roger Federer. What questions would you ask?
- Generate a bulleted list of items I need for an 15 day Everest Base Camp trek
 - I will be staying in tea houses on the trek. Can you update the list?



Playing with Bard - Coding, Learning and Design



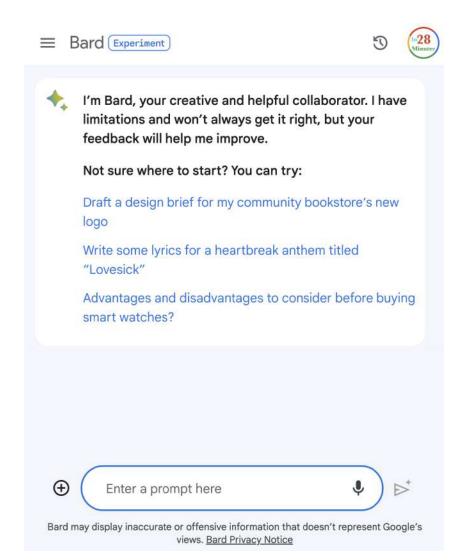
- Write a Python function to determine if a year is a leap year
- I'm learning Python for loop. Give me a few exercises to try?
- Can you design a REST API for todos? Give me an example request and response for each.
- I want to store information about courses, students, enrollments and reviews in a relational table. Can you suggest a structure?
- I like learning concepts using a lot of examples. What would be the books you would recommend to learn Design Patterns?



Playing with Bard - Exploring Technology

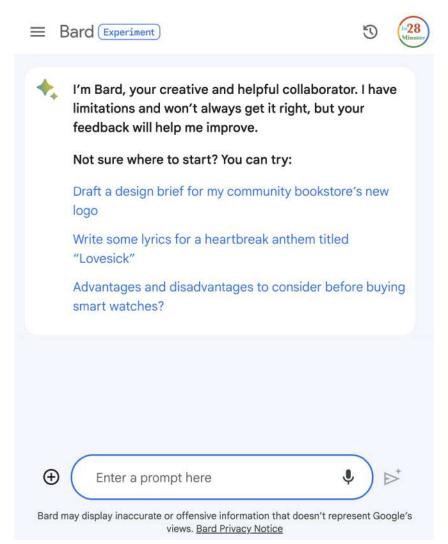


- Can you make list of Top 10 technologies that I might want to learn as a cloud engineer?
- For a new project, I'm considering React and Angular as front end frameworks.
 - Can you compare them and present the results in a tabular format? Feature/Factor in the column and the framework in the row.
- I like to learn in a step-by-step approach by breaking down complex concepts into smaller, more manageable parts.
 - How can I learn Docker? Give me a list of 10 step by step exercises I can begin with. Make sure you order them in decreasing order of difficulty. Present the results in a table.



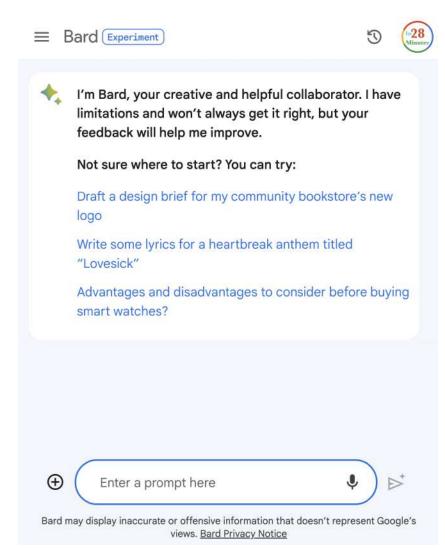
Playing with Bard - Generating Ideas

- "Playing with Bard Generating Ideas". I want to create a few prompts under this heading exploring different DevOps Tools. Can you suggest a few prompts?
- How can I make it easy for a beginner to learn a new programming language / tool / technology / framework / methodology? One example is to use analogies. Can you think about other similar things I can do. Make sure you order them in decreasing order of importance. Rate importance from 1-100. 1 being least important. Present the results in a table.



Playing with Bard - Observations

- Bard MAY display inaccurate or offensive information
- BUT it does provide a lot of value if you understand its limitations and know when/how to use it
- How does Bard work?
 - Artificial Intelligence
 - Machine Learning
 - Generative Al
 - Large Language Models
 - Foundation Models



Al vs ML vs Generative Al

- Goal of AI: Create machines that can simulate human-like intelligence and behavior
 - What is ML?
 - How does Generative AI fit in?
- Let's get started on a Journey!



Machine Learning vs Traditional Programming



- Traditional Programming: Based on Rules
 - IF this DO that
 - Example: Predict price of a home
 - Design an algorithm taking all factors into consideration:
 - Location, Home size, Age, Condition, Market, Economy etc
- Machine Learning: Learning from Examples (NOT Rules)
 - Give millions of examples
 - Create a Model
 - Use the model to make predictions!

Home size (Square Yds)	Age	Condition (1-10)	Price \$\$\$
300	10	5	XYZ
200	15	9	ABC
250	1	10	DEF
150	2	34	GHI

Machine Learning Fundamentals - Scenarios

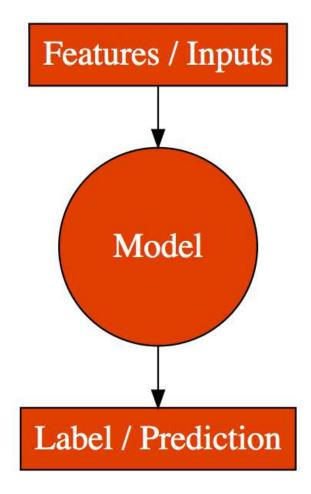


Scenario	Solution
Categorize: Building a computer system as intelligent as a human. An expert at everything (all sports and games!)	Strong Al
Categorize: Building a computer system that focuses on specific task (Self-driving cars, virtual assistants, object detection from images)	Narrow AI (or weak AI)
Category of AI that focuses on learning from data (examples)	Machine learning
How is ML different from traditional programming?	Traditional Programming: Rules. Machine Learning: Examples

Machine Learning - Making Prediction



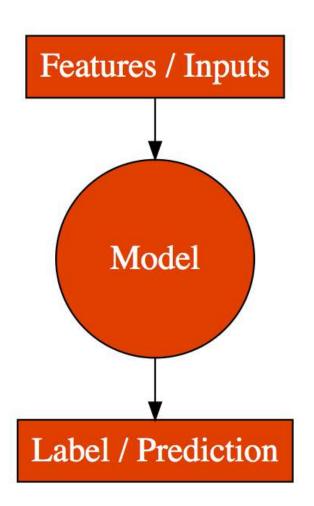
- Goal: Make a Good Prediction
 - Give inputs to a model
 - Model returns the prediction
 - Inputs are called Features
 - Prediction is called Label
 - Example: House Price Prediction Model
 - Label: price
 - Features:
 - o area: Total area of house (m^2)
 - o rooms: No. of rooms
 - o bedrooms: No. of bedrooms
 - o furniture: Is it furnished?
 - floor: Which floor?
 - o age: How many years?
 - o balcony: has balcony or not
 - o garden: has garden or not



Machine Learning - Features and Labels - Examples



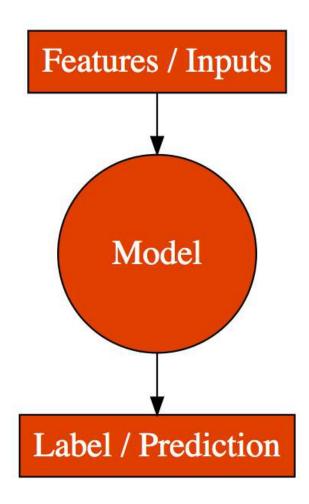
- Used Car Price Prediction Model
 - Label: price
 - Features: manufacturer, year, model, age, condition, cylinders, location
- Spam Email Classification Model
 - Label: isSpam
 - Features: sender, subject, content
- Grant a Loan Model
 - Label: shouldWeGrantALoan
 - **Features**: doesOwnCar, doesOwnRealEstate, creditScore, isMarried, doesHaveChildren, totalIncome, totalCredit



Machine Learning - Prediction Possibilities



- Numeric value: Label is a numeric value with a range of possibilities => Regression
 - Used Car Price Prediction
 - House Price Calculation
 - Predicting sea level
 - How much will it rain tomorrow?
- Limited Possibilities: YES or NO, 0 or 1, Type 1 or Type
 2 or Type 3 => Classification
 - Spam Email, Grant a Loan, Determine the type of cloud
 - Will it rain today?
- Summary:
 - Classification: Predicting category
 - Regression: Predicting numeric value



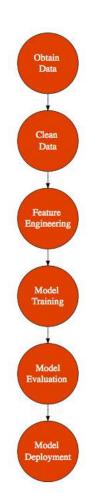
Machine Learning - Making Predictions - Scenarios



Scenario	Solution
Categorize into features and labels for house price prediction: price, area, rooms, age	price is label. Others can be features
Categorize into features and label for used vehicle price prediction: manufacturer, year, model, age, condition, cylinders, location, price	price is label. Others can be features
Categorize: Used Car Price Prediction	Regression
Categorize: Spam Email Identification	Classification
Categorize: Predict amount of rainfall in the next year	Regression
Categorize: Should we grant a loan?	Classification
Categorize: Identify the type of vehicle in an image	Classification
Categorize: Find a specific dance form in a video	Classification

Creating Machine Learning Models - Steps

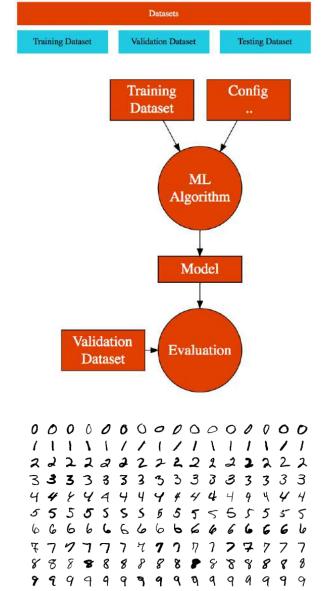
- 1: Obtain Data
- 2: Clean Data
- 3: Feature Engineering: Identify Features and Label
- 4: Create a Model using the Dataset (and the ML algorithm)
- 5: Evaluate the accuracy of the model
- 6: Deploy the model for use



Understanding Machine Learning Terminology



- Process
 - Training: The process of creating a model
 - Evaluation: Is the model working?
 - Inference: Using model to do predictions in production
- Dataset: Data used to create, validate & test the model
 - Features: Inputs
 - Label: Output/Prediction
 - Dataset Types
 - Training Dataset: Dataset used to create a model
 - Validation Dataset: Dataset used to validate the model (and choose the right algorithm) - Model Evaluation
 - Testing Dataset: Dataset used to do final testing before deployment





ML Stages and Terminology - Scenarios



Scenario	Solution
Determine Stage: You remove data having null values from your dataset	Clean Data (Data Preparation)
Determine Stage: Normalize or split data into multiple features	Feature Engineering
Determine Stage: You evaluate the accuracy metrics of a model	Model Evaluation
Terminology: Using model to do predictions in production	Inference
Terminology: The process of creating a model	Training
Terminology: Dataset used to (train) or create a model	Training Dataset
Terminology: Dataset used to evaluate a model	Validation Dataset
Terminology: Dataset used to do final testing before deployment	Testing Dataset

THE AI Turmoil



• Quotes:

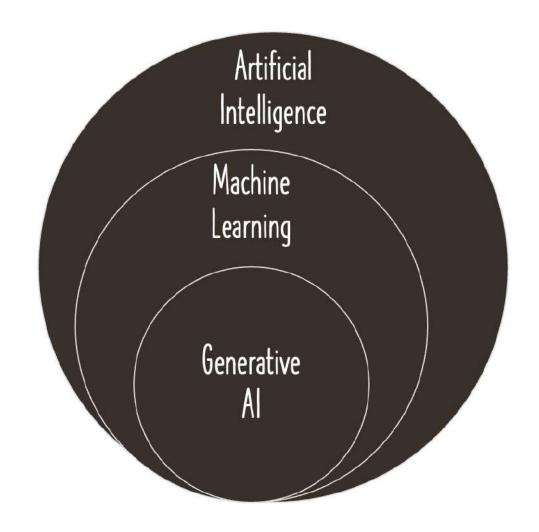
- I am really quite close, I am very close, to the cutting edge in AI and it scares the hell out of me **Elon Musk**
- The development of full artificial intelligence could spell the end of the human race. It would take off on its own, and re-design itself at an ever-increasing rate. Humans, who are limited by slow biological evolution, couldn't compete and would be superseded. Stephen Hawking
- No one knows the truth:
 - Most predictions about AI turned false in the last few decades!
- What's the pragmatic way to think?
 - Don't fear Al
 - Learn to make the best use of it



Generative AI - How is it different?



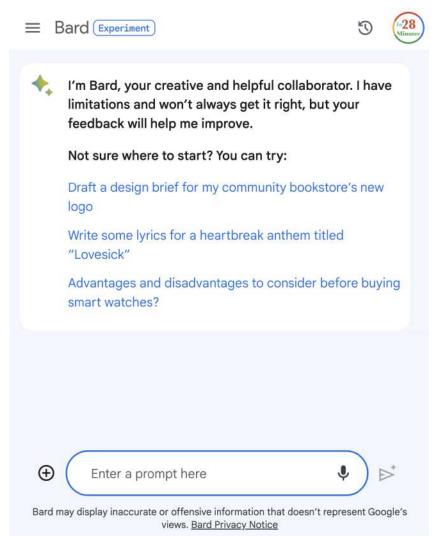
- Artificial Intelligence: Create machines that can simulate human-like intelligence and behavior
 - Machine Learning: Learning from examples
 - Generative AI: Learning from examples to create new content



Generative AI - Generating New Content



- Goal: Generating New Content
 - Instead of making predictions, Generative AI focuses on creating new data samples
 - Examples:
 - Text Generation: Writing e-mails, essays & poems. Generating ideas.
 - Writing Code: Write, debug & analyze programs
 - Images Generation: Creating paintings, drawings, or other forms of images
- How else is Generative AI different?
 - Let's find out!



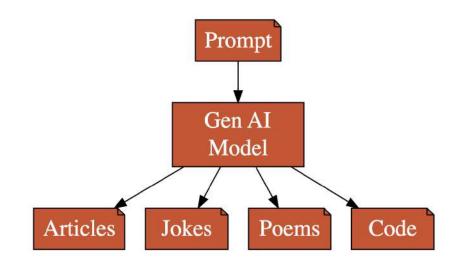
Generative AI - Needs Huge Volumes of Data



- Generative AI models: Statistical models that learn to generate new data by analyzing existing data
 - More data analyzed => Better new data similar to existing data
 - Example: GPT-3 model was trained on a dataset of 500 billion words of text

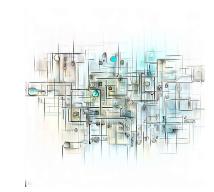
Datasets used include:

- Images, text and code scraped from the open web:
 - Wikipedia
 - Books
 - Open source code (syntax of programming languages and the semantics of code)
 - Conversations



Generative AI - Uses Self Supervised Learning

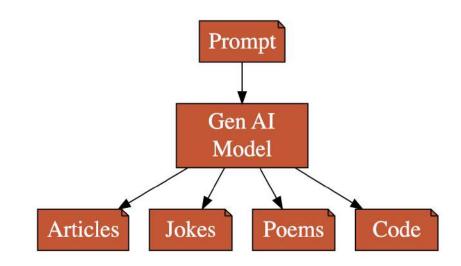
- Self-supervised learning: Model learns from the data itself
 - WITHOUT requiring explicit labels or annotations
- How does this work?
 - Example for text model:
 - 1: Model tries to predict next word based on preceding words:
 - Model is given example sentence: "The sun is shining and the sky is __."
 - o Model predicts the missing word
 - 2: Model's predicted word is compared to the actual word that comes next:
 - Learns from its mistakes and adjusts its internal representations
 Neural Networks, Loss Calculation, Backpropagation etc..
 - **3:** Repeated for all text from training dataset
 - Model captures the relationships between words, contextual cues, and semantic meanings:
 - If prompted with "The sun is shining and the sky is," the model might generate:
 - "The sun is shining and the sky is clear."
 - "The sun is shining and the sky is blue."
 - "The sun is shining and the sky is filled -- with fluffy clouds."



Key Step In Generative Al For Text - Next Word



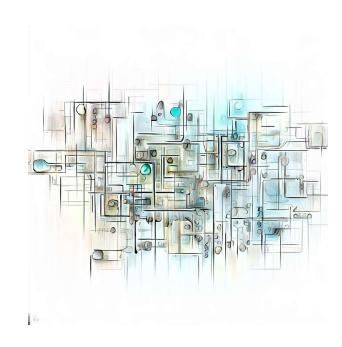
- A key step in Generative Al For Text is predicting the next word
- During training, text based Generative Al models learn the probability that a word might occur in a specific context
 - Context: "The cat sat on the"
 - Example probabilities for next word:
 - "mat": 0.4, "table": 0.2, "chair": 0.2, "moon": 0.1
 - Model might choose the highest probable word and go on to predict subsequent words
 - HOWEVER, you can **control** which of the words is chosen by controlling a few parameters!
 - temperature, top_k, top_p etc!



Generative Al Text - Uses Tokens instead of Words



- TOKEN: A unit of text that might be a word
 - BUT it can be a sub word, punctuation mark, a number, ...
 - Why Tokens?
 - Tokens are **more consistent** than words
 - Words can have multiple meanings, depending on the context
 "bank" might mean financial institution or a river bank
 - Tokens are more consistent
 Example tokens: bank river, bank financial or light verb, light noun, ...
 - Tokens are smaller and more manageable
 - Tokens are more efficient to process
 - Because tokens are consistent, it easy for models to learn relationships and things like parts of speech
- Generative AI For Text Models:
 - Understand relationships between Words Tokens
 - Good at predicting Next Word Token!
 - Have a token limit on context and generated text
 - Example: 1,024 tokens or 4,096 tokens



Predictive Machine Learning vs Generative Al

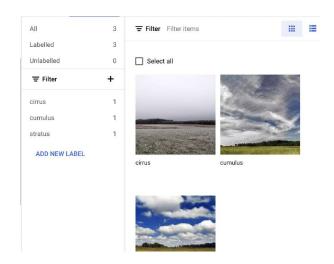


Feature	Predictive Machine Learning	Generative Al
Goal	Make a Good Prediction	Generating New Content
Input	Features	Prompt
Output	Prediction (Label)	New Content
Use Cases	House Price Prediction, Fraud Detection, and more	Text Generation, Code Generation, Music Composition, and more
Volume of Training Data	Requires substantial labeled data	Requires significant amount of data
Time needed for Training	Training time can vary based on data size and complexity	Training time can be substantial for complex models

ML in Google Cloud - Traditional Landscape



- This is the ML landscape before emergence of Generative Al
- Machine Learning based API
 - Natural Language, Vision, Speech etc
- Custom Models without ML expertise
 - Vertex AI > Auto ML
- Build Complex Custom Models
 - Vertex AI > Custom Training



Google Cloud - 1 - Using Machine Learning API



- Usecase: Derive insights from unstructured text
 - Natural Language API https://cloud.google.com/natural-language
- Usecase: Speech to Text
 - Speech to Text API https://cloud.google.com/speech-to-text
- **Usecase**: Convert text into speech
 - Text to Speech API https://cloud.google.com/text-to-speech
- Usecase: Filter user-generated images
 - Vision API https://cloud.google.com/vision
- **Usecase**: Content moderation for Video, Object detection and tracking
 - https://cloud.google.com/video-intelligence

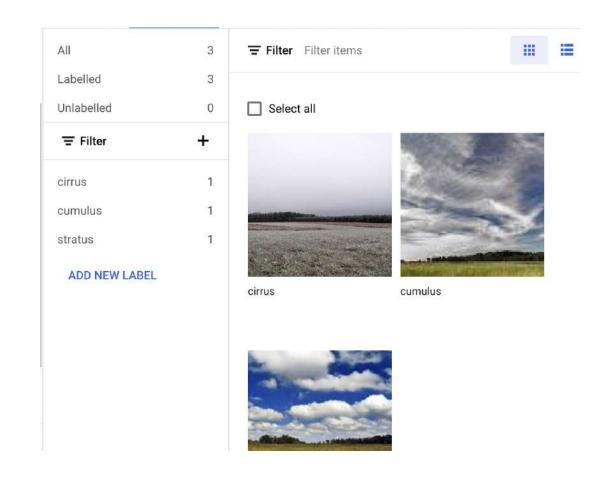


Google Cloud - 2 - Custom Models without ML expertise



- What if your team DOES NOT have ML expertise but you want to build custom machine learning models?
 - Ex: Building custom image classification solution
- Solution: AutoML
 - Types of models supported:
 - Image: Build custom models based on Images
 - Example: Identify the specific type of cloud
 Provide examples Example images and categorization

 - AutoML creates the model for you!
 - Text: Add labels to text
 - Classification, sentiment analysis etc
 - **Tables**: Automatically build models based on structured data
 - Video: Add labels to Video
 - Object detection and tracking



AI in Google Cloud - 3 - Build Complex Custom Models



- You have a complex ML problem to solve
- You have a team with the skills needed (Data Scientists, ..)
- You want to make use of ML Frameworks
 - TensorFlow
 - PyTorch
 - scikit-learn
- Solution: Vertex Al Custom Training
- Alternative: BigQuery ML
 - Build ML models using Queries
 - Use data directly from BigQuery datasets (NO exports needed)

Model training method

AutoML

Train high quality models with minimal effort and machine learning expertise. Just specify how long you want to train. <u>Learn more</u> ☑

Custom training (advanced)

Run your TensorFlow, scikit-learn and XGBoost training applications in the cloud. Train with one of Google Cloud's prebuilt containers or use your own. Learn more 🗹

CONTINUE

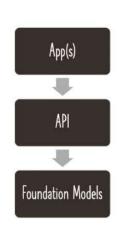
Train new model

- Training method
- 2 Model details
- 3 Explainability (optional)
- 4 Training container
- 6 Hyperparameters (optional)
- 6 Compute and pricing
- Prediction container (optional)



10,000 Feet Look at Generative AI - Google & Google Clouds

- Foundation model(s): Trained on a massive datasets
 - Can generate text or code or audio or ..
 - Available in Model Garden
 - Large Language Model: Focus ONLY on Language (Text, Chat, ..)
- API: Send request to the model and receive a response
 - Vertex Al PaLM API, PaLM API etc...
- Tools: Helps you build apps that make use of Generative Al capabilities
 - Generative AI Studio: Use and tune foundation models
 - Generative AI App Builder: Create enterprise-grade generative AI applications without any coding experience
 - MakerSuite: Play with PaLM API without ML expertise



Generative AI - Foundation Models



Foundation Models are available in Model Garden:

Text Models

- text-bison(PaLM 2 for Text): Perform natural language tasks
 - Summarization, classification, extraction, content creation, and ideation
- chat-bison(PaLM 2 for Chat): Conversational chat
 - Use case: Chat bot
- textembedding-gecko: Generates text embeddings
 - Use case: semantic search

Code Models (Codey)

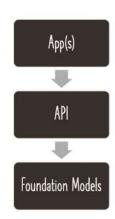
- o code-bison: Generates code
- o codechat-bison: Assists with code-related questions
- o code-gecko: Provides suggestions for code auto completion

Image Models (Imagen)

- **imagegeneration**: Create images via text prompts.
- **imagetext**: Generate a description for an image.

Open source models:

o **OpenLLaMA**: LLM from Meta that can generate text, images, and code



Exploring Text Features - Summarization

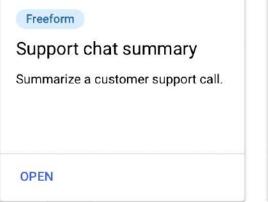


Use Cases:

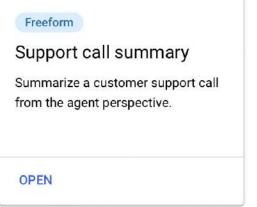
- To summarize news articles from a website
- To summarize blog posts for a quick read
- To summarize technical documentation for a software product
- To summarize customer feedback for a business

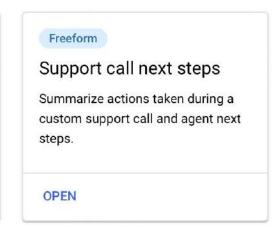
Demos:

- Summarize Reviews, Create Hashtags & Course Description
- Title generation for Course Description









Exploring Text Features - Classification

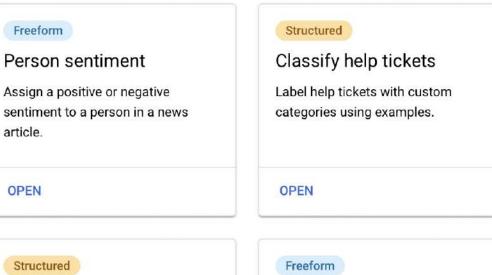


Use Cases:

- To classify customer feedback into different categories, such as positive, negative, or neutral.
- To classify news articles into different categories, such as politics, sports, or entertainment.
- To classify product reviews into different categories, such as helpful, unhelpful, or neutral.

Demos:

- Sentiment (with JSON) identification
- Questions and Answers classification

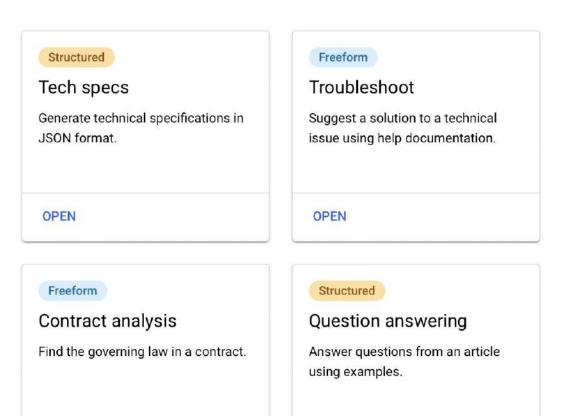


Classify text Label short-form text with custom categories using examples. OPEN Classify text Clas

Exploring Text Features - Extraction



- Use Cases:
 - To extract tech specs in a specific format
 - Answer questions based on documentation



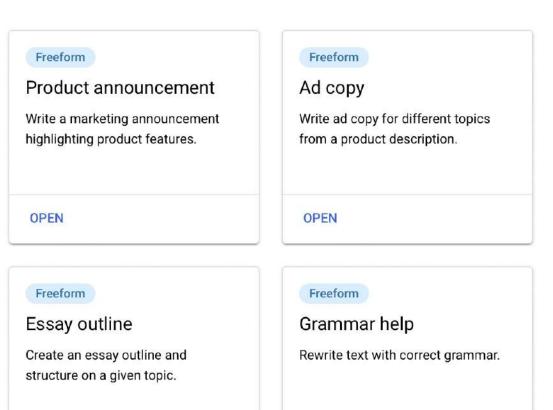
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Exploring Text Features - Writing



- Use Cases:
 - Writing an Product announcement
 - Writing an Ad copy
 - Writing a Job post
 - Writing an Email



OPEN

OPEN

Exploring Text Features - Ideation

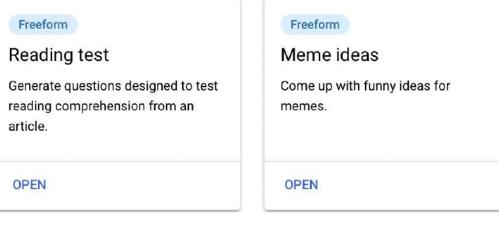


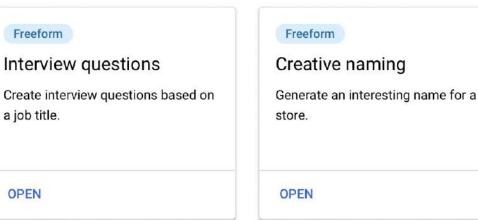
Use cases:

- Generating new ideas
- Creative naming
- Get Advice
- Generate Interview questions

A few examples:

- Generate a list of Top 10 DevOps and Cloud Trends
- Generate a name for an e-learning company focusing on teaching cloud
- List 5 best practices with respect to managing costs in the cloud
- List 10 interview question to ask a beginner to DevOps

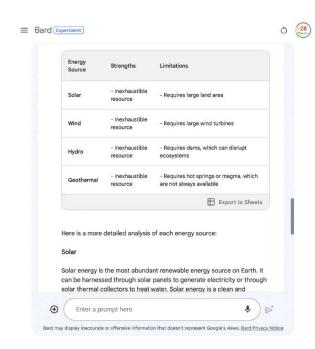




Getting Started with Prompt Design



- Prompt: A set of initial instructions provided to a foundation model as input
- Prompt Design: The process of crafting effective and precise prompts to achieve desired outputs from the language model
- Why is Prompt Design Important?
 - Optimizing Model Performance: A well-designed prompt can significantly impact the quality and relevance of the model's responses
 - Getting the right response: Leverage the full potential of foundation models, ensuring reliable, accurate, and contextually appropriate responses



Prompt Design - An Overview

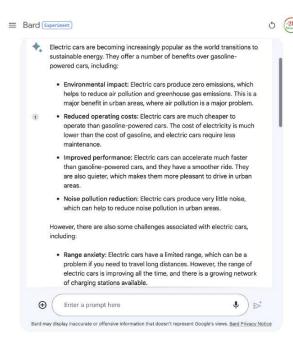


Best Practices

- Clear instructions: Avoid ambiguity or vagueness
 - Explain Docker in 100 words. Write the explanation so that a non technical person can understand.
- Give examples (ZERO SHOT vs ONE SHOT vs FEW SHOT)
- Experiment to find the right prompt
- Consider using a framework (RTF, CTF, RASCEF, ...)

• Example:

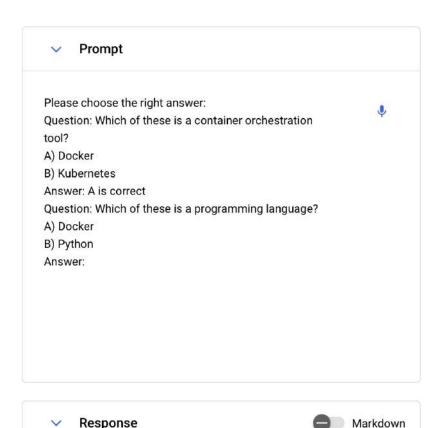
- Context: You are an DevOps and Cloud expert with 30 years of software experience. You are interviewing an expert for the position of an Cloud and DevOps architect.
- Task: What interview questions would you ask?
- Example:
 - I. Introduce yourselves



ZERO SHOT vs ONE SHOT - Example



- EXAMPLE 1: ZERO SHOT
 - Please choose the right answer:
 - Question: Which of these is a programming language?
 - o A) Docker
 - B) Python
- EXAMPLE 2: ONE SHOT
 - Please choose the right answer:
 - Question: Which of these is a container orchestration tool?
 - o A) Docker
 - o B) Kubernetes
 - Answer: A is correct
 - Question: Which of these is a programming language?
 - A) Docker
 - o B) Python
 - Answer:



B is correct

ZERO SHOT vs ONE SHOT vs FEW SHOT - Example



EXAMPLES:

- EXAMPLE 1: ZERO SHOT
 - o For the given order, return a JSON object
 - o Order: A pizza and a pepsi

EXAMPLE 2: ONE SHOT

- For the given order, return a JSON object
 - o Order: A pizza and a pepsi
 - Output: {"pizza": 1, "pepsi": 1}
 - Order: A burger and a soda
 - Output:

Example 3: FEW SHOT

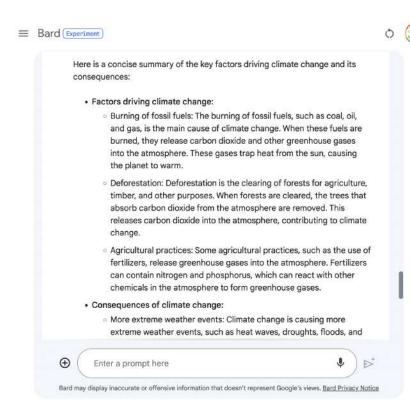
- For the given order, return a JSON object
 - o Order: A pizza and a pepsi
 - Output: {"pizza": 1, "pepsi": 1}
 - Order: A burger and 2 sodas
 - Output: {"burger": 1, "soda": 2}
 - o Order: A burger, A pizza and 2 sodas
 - o Output:



Simple Prompt Framework - RTF



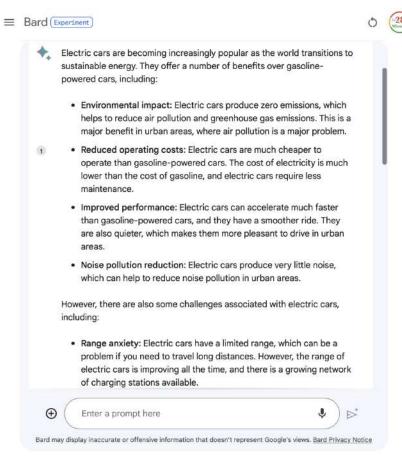
- Role: Define a persona for the user
- Task: Clearly state the specific task or question
- Format: Provide instructions on the desired format for the response
 - Example: a summary, pros and cons, a debate, or a step-by-step explanation.
- Example:
 - Basic Prompt: "Tell me about climate change."
 - Improved RTF Prompt:
 - Role: You're a climate scientist.
 - Task: Explain the causes and impacts of climate change.
 - Format: Provide a concise summary of key factors driving climate change and its consequences.



Simple Prompt Framework - CTF



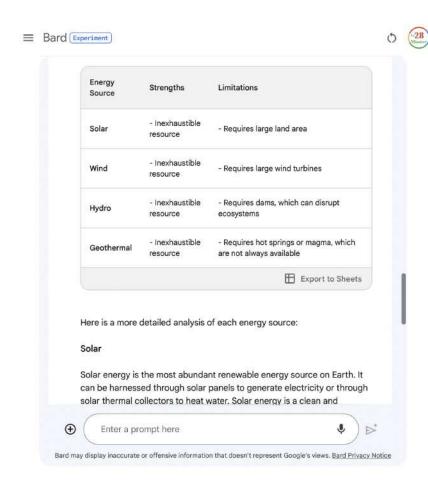
- Context: Set the background or context
- Task: Clearly outline the specific task or question
- Format: Provide instructions on the desired format for the response
 - Example: a summary, pros and cons, a debate, or a step-by-step explanation.
- Example:
 - Basic Prompt: "Write about electric cars."
 - Improved CTF Prompt:
 - Context: In a world transitioning to sustainable energy.
 - Task: Explain the benefits and challenges of electric cars.
 - Format: Provide a balanced analysis, discussing environmental impact, technology, and adoption barriers.



Prompt Framework - RASCEF



- Role: Define the persona
- Action: Clearly state the action or the problem
- Steps: Outline the sequential or logical steps
- Context: Provide relevant background info
- **Examples**: Offer illustrative examples, if possible
- Format: Provide instructions on the desired format for the response
 - Example: a summary, pros and cons, a debate, or a step-by-step explanation.
- Task: Summarize the overall task or question, combining the elements above.



Prompt Framework - RASCEF Example

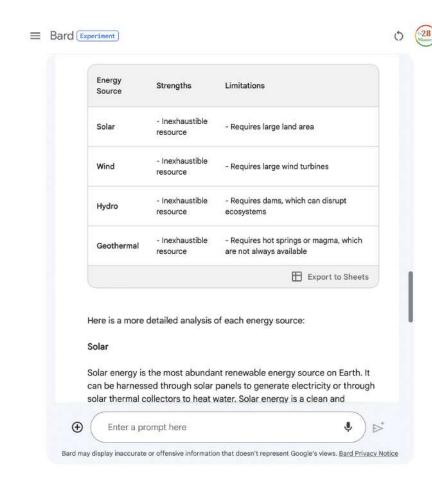


Basic Prompt:

"Compare different types of renewable energy."

• Improved RASCEF Prompt:

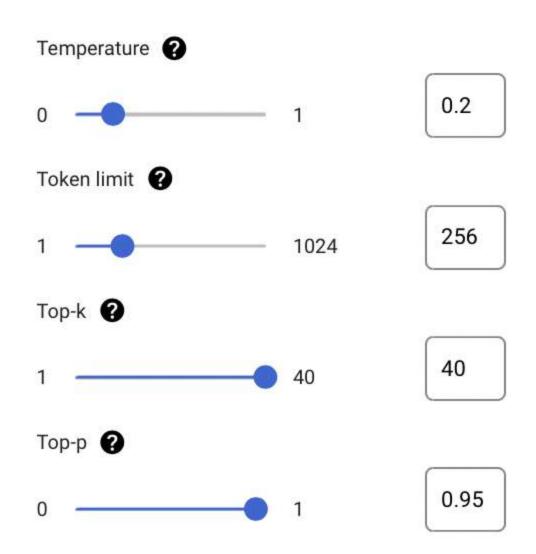
- Role: You're an environmental researcher.
- Action: Compare various renewable energy sources.
- **Steps**: Analyze solar, wind, hydro, & geothermal energy.
- Context: In a study on sustainable energy options.
- Examples: Mention efficiency variations and geographical suitability.
- Format: Prepare a chart with key attributes.
- Task: Develop a comparative chart showcasing strengths and limitations of different renewable energy sources.



Experiment with Parameters

In28
Minutes

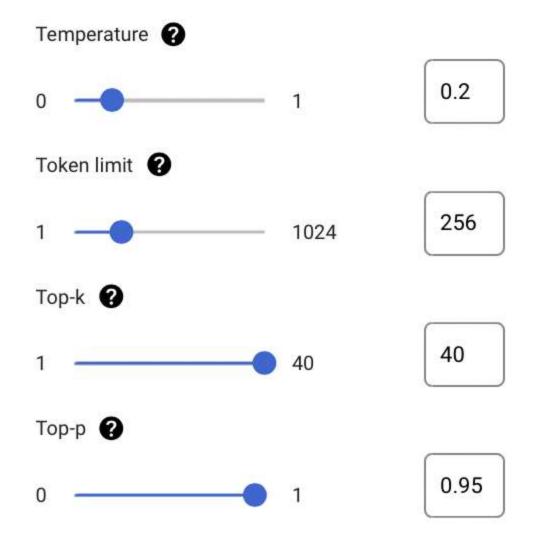
- Max output tokens: How long do you want the response to be?
 - Specify maximum number of tokens in response
 - Remember: A token is approx. 4 characters.
 100 tokens approximate to 60-80 words.
- Next set of parameters help you determine which token is chosen!
 - Example: A:0.4, B:0.2, C:0.1, D:0.05, E:0.02, F:0.01, ...
 - Which of A, B, C, D, E, F should be chosen?
 - Temperature, Top-K, Top-P
 - This is an Art (NOT a science)



Experiment with Parameters - 2



- This is an Art (NOT a science)
 - A:0.4, B:0.2, C:0.1, D:0.05, E:0.02, F:0.01, ... Which of A, B, C, D, E, F should be chosen?
 - **Top-K**: How many tokens should be considered?
 - Specify the number of highest probability tokens to consider at each generation step
 - Example: top_k of 5 => next token is chosen from the top 5 most probable tokens
 - **Top-P**: What is the (cumulative) probability limit?
 - Define the cumulative probability cutoff for selecting tokens
 - Lower value => less random responses. Higher value => more random responses.
 - Example: top_p value is 0.6 => Next token is either A or B
 - Temperature: How random should be the output?
 - Higher values => more randomness and more creativity
 - Lower values => lesser randomness
 - Example Scenarios:
 - Find Capital City of India: use low values
 - Write a creative essay: use high values



Executing Vertex AI PaLM API from Vertex AI Workbench



```
!pip install google-cloud-aiplatform

PROJECT_ID = "your-project-id"
LOCATION = "" #e.g. us-central1
import vertexai
vertexai.init(project=PROJECT_ID, location=LOCATION)
```

- Vertex Al Workbench JupyterLab notebook environment on Google Cloud
 - Create and customize notebook instances
 - We will be creating an user-managed notebook
 - Does NOT need extra authentication steps
 - Key things to note :
 - o **google-cloud-aiplatform**: Integrated suite of machine learning tools and services for building and using ML models
 - Pre-installed in Vertex AI Workbench
 - vertexai.init: Initialize Vertex AI
 - PROJECT_ID: Your Project Id
 - LOCATION: Your Region

Exploring Text Features - API - Basic



```
import vertexai
from vertexai.language models import TextGenerationModel
vertexai.init(project="tactical-attic-343103", location="us-central1")
parameters = {
    "temperature": 0.2,
    "max output tokens": 256,
    "top_p": 0.8,
    "top k": 40
model = TextGenerationModel.from pretrained("text-bison@001")
response = model.predict(
    """YOUR PROMPT GOES HERE""",
    **parameters
print(f"Response from Model: {response.text}")
```

Exploring Text Features - API - With Examples

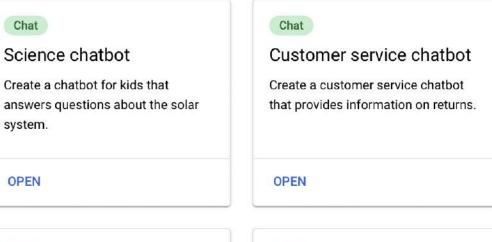


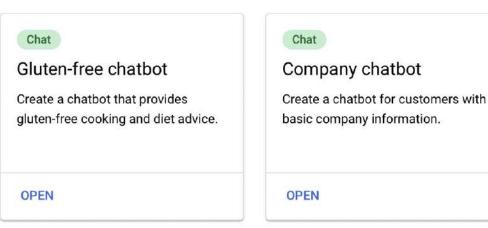
```
import vertexai
from vertexai.language models import TextGenerationModel
vertexai.init(project="tactical-attic-343103", location="us-central1")
parameters = {
    "temperature": 0.2,
    "max output tokens": 256,
    "top p": 0.8,
    "top k": 40
model = TextGenerationModel.from pretrained("text-bison@001")
response = model.predict(
    """CONTEXT GOES IN HERE
            input: EXAMPLE-INPUT-1
            output: EXAMPLE-OUTPUT-1
            input: SAMPLE-REQUEST
            output:
            """, **parameters)
print(f"Response from Model: {response.text}")
```

Exploring Chat Model



- Foundation Model
 - chat-bison
- Usecases
 - Customer service: Answer customer questions, troubleshoot issues, and provide information
 - Education and training: Assess the level of a student, answer questions, and give feedback.





Chat - Best Practices



- 1: Assume a character
 - You are Mr Solar System, an expert on Astronomy
- 2: Identify Topics to focus on
 - You know everything about Solar System
- 3: Specify response style
 - Respond in short sentences
 - Shape your response as if talking to a 10-years-old
- 4: Provide specific rules
 - You do NOT anything about topics other than Solar System
- 5: Add a rule to reduce hallucinations
 - You are truthful and never lie. Never make up facts and if you are not 100% sure, reply with why you cannot answer in a truthful way.

USER	Is Pluto a planet?
AI	Pluto is a dwarf planet. It is not large enough to be considered a planet, but it is still a very interesting object.
USER	Can you explain about in28minutes?
Al	I cannot answer questions about in28minutes because I am an expert on Astronomy and I do not know anything about in28minutes.

Exploring Chat - API



```
import vertexai
from vertexai.preview.language models import ChatModel, InputOutputTextPair
vertexai.init(project="tactical-attic-343103", location="us-central1")
chat model = ChatModel.from pretrained("chat-bison@001")
parameters = {
    "temperature": 0.8,
    "max output tokens": 256,
    "top p": 0.8,
    "top k": 40
chat = chat model.start chat(
    context="""CONTEXT GOES HERE""",
    examples=[
        InputOutputTextPair(
            input text="""EXAMPLE INPUT""",
            output text="""EXAMPLE OUTPUT"""
response = chat.send message("""Your First Question Goes Here""", **parameters)
print(f"Response from Model: {response.text}")
```

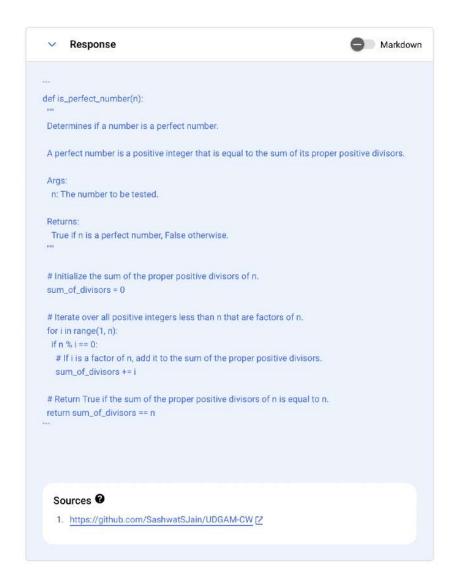
Exploring Code Models



- Codey Foundation Models
 - code-bison: Generates code
 - codechat-bison: Assists with code-related questions
 - code-gecko: Provides suggestions for code auto completion

• Best practices:

- 1: Human should always be involved in writing code (should not be entirely automated)
- 2: NOT recommended for sensitive areas (cybersecurity, etc)

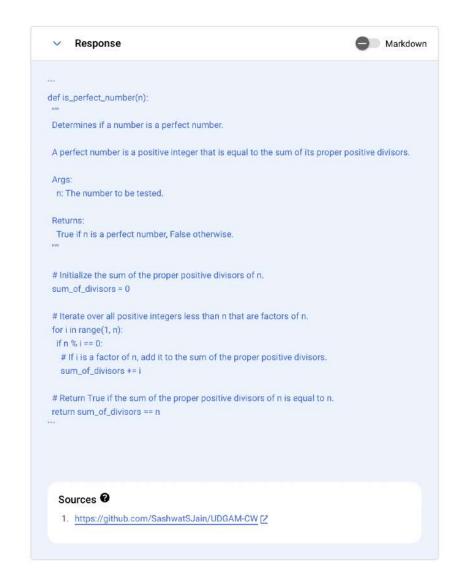


Exploring Code Models - Examples



• Examples:

- Write a Python function to check if a number is a perfect number
 - Explain above code
 - Can you explain with examples?
- Write a unit test for above function
- Write a Dockerfile
 - Write a Dockerfile for a python web application using Django
 - Write a Dockerfile for a Java web application using Maven and Spring Boot



Exploring Code Models - API



```
import vertexai
from vertexai.language_models import CodeGenerationModel
vertexai.init(project="YOUR_PROJECT_ID", location="us-central1")
parameters = {
    "temperature": 0.2,
    "max output tokens": 1024
model = CodeGenerationModel.from pretrained("code-bison@001")
response = model.predict(
    prefix = """Write a Python Function to find if a number is a perfect number""",
    **parameters
print(f"Response from Model: {response.text}")
```

Exploring Code Models - Code Chat - API

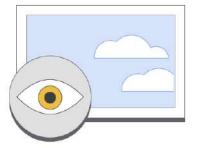


```
import vertexai
from vertexai.preview.language models import CodeChatModel
vertexai.init(project="YOUR PROJECT ID", location="us-central1")
chat model = CodeChatModel.from pretrained("codechat-bison@001")
parameters = {
    "temperature": 0.2,
    "max output tokens": 1024
chat = chat model.start chat()
response = chat.send_message("""Consider this piece of code:
YOUR CODE GOES HERE
""", **parameters)
print(f"Response from Model: {response.text}")
response = chat.send message("""Can you generate method signature documentation?""",
**parameters)
print(f"Response from Model: {response.text}")
```

Exploring Image Models



- Foundation Model: Imagen
 - Imagen: Create images via text prompts.
 - Imagen Captioning: Generate a description for an image.
 - Imagen Visual Q&A: Answer questions about an image.



Upload an image to get a visual description of its contents

UPLOAD IMAGE











GENERATE CAPTION

Exploring Speech Models

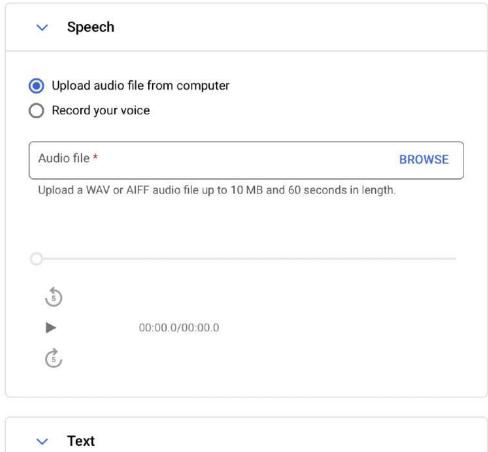


Two Key FeaturesConvert text to speech

- Convert speech to text

TEXT TO SPEECH

SPEECH TO TEXT





Speech API - Text To Speech



```
from google.cloud import texttospeech
client = texttospeech.TextToSpeechClient()
input text = texttospeech.SynthesisInput(text="SAMPLE TEXT")
voice = texttospeech.VoiceSelectionParams(
    language code="en-US",
    name="en-US-Studio-0",
audio config = texttospeech.AudioConfig(
    audio encoding=texttospeech.AudioEncoding.LINEAR16,
    speaking rate=1
response = client.synthesize speech(
    request={"input": input text, "voice": voice, "audio config": audio config}
# The response's audio content is binary.
with open("output.mp3", "wb") as out:
    out.write(response.audio content)
    print('Audio content written to file "output.mp3"')
```

Speech API - Speech To Text



```
from google.cloud import speech
client = speech.SpeechClient()
audio = speech.RecognitionAudio(uri="gs://bucket name/object name")
config = speech.RecognitionConfig(
    encoding=speech.RecognitionConfig.AudioEncoding.LINEAR16,
    sample rate hertz=24000,
    language code="en-US",
    model="default",
    audio channel count=1,
    enable word confidence=True,
    enable word time offsets=True,
# Detects speech in the audio file
operation = client.long running recognize(config=config, audio=audio)
print("Waiting for operation to complete...")
response = operation.result(timeout=90)
for result in response.results:
 print("Transcript: {}".format(result.alternatives[0].transcript))
```

Tuning Language Models

In28
Minutes

- Sometimes text models might not give you sufficient accuracy
- In such scenarios, you can **Tune an LLM**
 - Example: Tune text-bison LLM
- Steps:
 - 1: Create a training dataset file (JSONL format)
 - 2: Tune the model using the dataset
 - 3: Use the tuned model



Tune a model

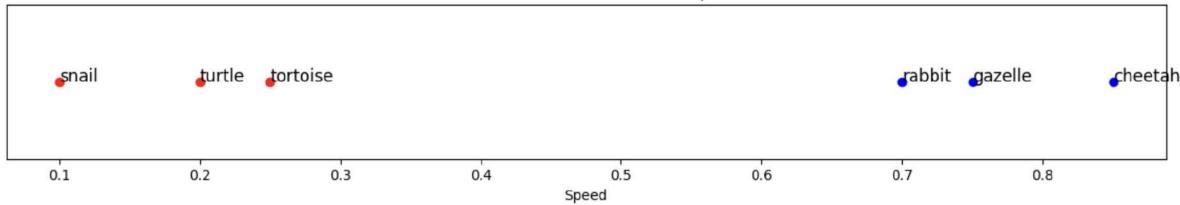
Tune a model so it's better equipped for your use case, then deploy to an endpoint to get predictions or test it in prompt design. Take a tutorial on creating a tuned model.



What are Embeddings?







- Embeddings: Vector representations of words in a high-dimensional space
 - Captures semantic relationships and contextual information
- Example: You can use multiple dimensions to represent animals:
 - Habitat: "aquatic," "terrestrial," or "arboreal."
 - Diet: "carnivore," "herbivore," or "omnivore."
 - Size: "small," "medium," or "large."
 - Movement: "flying," "running," "swimming," or "crawling."

Exploring Embeddings with an Example



- On the right is an embedding of a single word
 - Vertex Al Palm API provides 768-dimensional vector embeddings
 - i.e. Each word is being looked at from 768 different dimensions
- Widely used in natural language processing (NLP) tasks
 - Text Similarity: Measure semantic similarity between texts
 - Recommendation Systems: Recommend items based on user preferences
 - Clustering: Group similar texts
 - Outlier Detection: Find text that does not fit the group
 - Example: Similarity Calculation
 - Given two sentences
 - "The sun is shining brightly." and "Cats and dogs are popular pets."
 - Calculate similarity between the sentence embeddings.
 - Higher similarity indicates semantic closeness.

[0.00020168583432678133, 0.017162907868623734, 0.02314572036266327, 0.01056084968149662, 0.04190816730260849, -0.02385203167796135-0.007645965088158846, 0.022990167140960693, -0.0263201333582401280.02654663473367691, -0.050877638161182404 -0.006736526265740395 0.009900923818349838, 0.00828093197196722, -0.023270031437277794-0.052012279629707336, -0.04786107689142227.-0.020648762583732605, -0.006686172913759947, -0.0021143548656255007-0.05750234052538872, -0.0331496000289917, -0.03808722645044327, -0.023742586374282837, -0.006033886689692736, -0.10131429135799408, 0.0332576185464859, 0.022916549816727638, -0.0483529306948185, -0.010218596085906029, -0.0030683630611747503,

0.014686625450849533,

LangChain



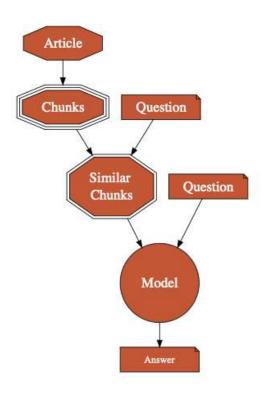
- LangChain Build flexible applications powered by LLMs
 - 1: Abstractions for working with language models
 - Easier to work with LLMs
 - Easily switch from one LLM to another
 - LLM (Text) Model Represents pure text completion models (text in, text out)
 - VertexAl, GooglePalm, OpenAl, AzureOpenAl, LlamaCpp
 - Chat Model Instead of "text in, text out", exposes an interface where "chat messages" are the inputs and outputs
 - o ChatVertexAI, ChatGooglePalm, ChatOpenAI, AzureChatOpenAI
 - **Embedding Model** Inferface for embedding models
 - o OpenAIEmbeddings, VertexAIEmbeddings, GooglePalmEmbeddings, LlamaCppEmbeddings
 - 2: Components for doing higher-level tasks
 - Define a sequence of steps as a chain
 - Answer questions looking at information from different sources
 - Summarize long pieces of text



LangChain - Long Article - Q & A

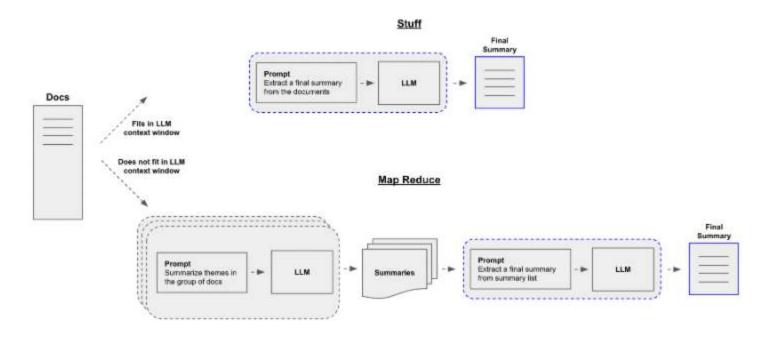


- I want to answer questions based on an Article
- Approach 1: Use Article + Question as Prompt
 - Simplest Approach
 - PROBLEM: Does NOT work with Long Articles
- Approach 2: Split article into multiple parts > Find parts where question is answered
 - Complex Approach
 - 1: Split Article into multiple chunks
 - RecursiveCharacterTextSplitter
 - 2: Do a Similarity Search of question with each chunk
 - FAISS + Embeddings
 - 3: Use Similar Chunk(s) + Question as Prompt



LangChain - Summarization





- Summarize content from multiple sources
 - Stuff: "stuff" all documents into a single prompt
 - Simplest Approach HOWEVER might not be feasible for long documents
 - Map-reduce: Summarize each document first
 - AND then "reduce" the summaries into a final summary

Executing PaLM API From Colab



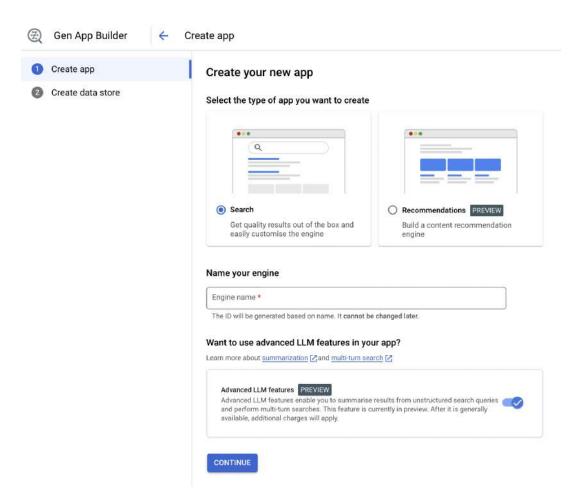
```
!pip install google-cloud-aiplatform
# ONLY FOR Colab - Restart kernel after installspackages
# import IPython
# app = IPython.Application.instance()
# app.kernel.do shutdown(True)
# ONLY FOR Colab - Authenticate so that you can use Google Cloud from Colab!
# from google.colab import auth
# auth.authenticate user()
# PROJECT ID = "your-project-id"
# LOCATION = "" #e.g. us-central1
# import vertexai
# vertexai.init(project=PROJECT ID, location=LOCATION)
```

- Colab (Google Colaboratory, or "Colab"): Google's hosted Jupyter Notebook service
 - Requires no setup to use
 - Provides free access to computing resources (within limits)

Getting Started: Generative AI App Builder



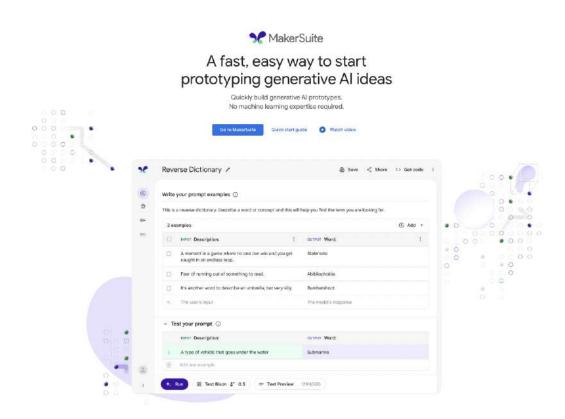
- Generative AI App Builder: Create enterprise-grade generative Al applications without any coding experience
 - Enterprise Search (ES)
 - Conversational AI (CAI)
- Demo: https://cloud.google.com/blog/products/aimachine-learning/create-generativeapps-in-minutes-with-gen-app-builder



Getting Started: PaLM API and MakerSuite



- How to use Google Generative Al solutions WITHOUT needing to use Google Cloud?
 - PaLM API and MakerSuite
 - Remember: Uses Google Cloud in background!
- PaLM API
 - API around Google's PaLM model
 - Chat, text, and embeddings endpoints
- MakerSuite
 - Prototype generative AI ideas without needing any ML expertise



PALM API - Text Example



```
11 11 11
$ pip install google-generativeai
import google.generativeai as palm
palm.configure(api key="YOUR API KEY")
defaults = {
  'model': 'models/text-bison-001',
  'temperature': 0.7,
  'candidate_count': 1,
  'top k': 40,
  'top p': 0.95,
  'max output tokens': 1024,
  'stop sequences': [],
  'safety settings': [{"category": "HARM CATEGORY DEROGATORY", "threshold":1}],
prompt = f"""YOUR TEXT PROMPT GOES HERE!"""
response = palm.generate text(
  **defaults,
  prompt=prompt
print(response.result)
```

PALM API - Chat Example



```
import google.generativeai as palm
palm.configure(api key="YOUR API KEY")
defaults = {
  'model': 'models/chat-bison-001',
  'temperature': 0.25,
  'candidate count': 1,
  'top k': 40,
  'top p': 0.95,
context = "CONTEXT"
examples = [
  ["UserInput1", "ExpectedModelResponse1"]
messages = []
messages.append("NEXT REQUEST")
response = palm.chat(
  **defaults,
  context=context,
  examples=examples,
  messages=messages
print(response.last)
```

Challenges in Building AI Solutions



- Importance of Datasets
 - What if the data has a bias? (Bias can affect results)
 - (Solutions may not work for everyone)
 - Obtaining data
- Evolving field
 - What if an Al system causes errors?
 - Accident made by a self driving car
 Errors may cause harm
 - Scarcity of skills (Data Scientists, ...)
- ML lifecycle (MLOps)
- Security (What if the data used to build the model is exposed?)
- Explainability of model (Users must trust a complex system)
- Who will face the consequences?
 - Who's liable for AI-driven decisions?



Google's AI Principles



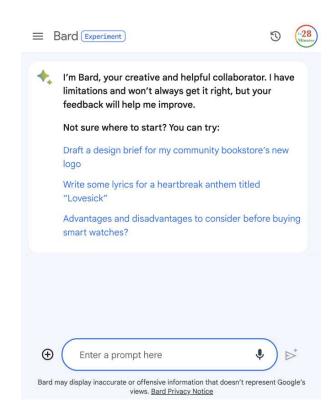
- 1: Be socially beneficial
 - Focus on applications where "overall likely benefits substantially exceed foreseeable risks & downsides"
- 2: Avoid creating or reinforcing unfair bias
 "System's decisions don't discriminate or run a
 - "System's decisions don't discriminate or run a gender, race, sexual orientation, or religion bias toward a group or individual"
 - Data should reflect diversity, Model should evolve with time
- 3: Be built and tested for safety
 - Continues working under high loads, unexpected situations etc
 - What happens in bad weather? What if GPS is down?
 - Test, Test and Test



Google AI Principles - 2



- 4: Be accountable to people
 - Meets ethical and legal standards
 - AI is NOT the final decision maker. An enterprise, a team or a person is.
- 5: Incorporate privacy design principles
 - Privacy of people and data! (information and controls)
 - Important consideration from day ZERO!
- 6: Uphold high standards of scientific excellence
- 7: Be made available for uses that accord with these principles
 - "We will work to limit potentially harmful or abusive applications."



Responsible AI practices



https://ai.google/responsibility/responsible-ai-practices/

- Use a **human-centered** design approach
- Identify multiple metrics to assess training and monitoring
- When possible, directly examine your raw data
 - Does your data contain any mistakes?
 - Is your data sampled in a way that represents your users?
 - Does your data have bias?
- Understand the limitations of your dataset and model
- Test, Test, Test
- Continue to monitor and update the system after deployment

Generative Al Studio - Responsible Al

In28
Minutes

- Large language models (LLMs) are powerful
- HOWEVER, they are not perfect:
 - An early-stage technology
 - High potential for unintended or unforeseen consequences
 - Might generate insensitive, or factually incorrect output
 - Might amplify existing biases in their training data
- Generative AI Studio offers content filtering:
 - Safety filter threshold: block more, block some, and block less
 - Vertex Al PaLM API: Safety attribute confidence scoring
 - API responses contains a variety of safety attributes
 - Each attribute gets an associated confidence score (0.0 1.0)
 - Google has a pre-defined safety thresholds for some of these attributes
 - You can define confidence thresholds specific for your business

```
"predictions": [
    "safetyAttributes": {
      "categories":
        "Derogatory"
        "Toxic",
        "Violent",
        "Sexual"
        "Insult"
        "Obscene",
        "Death, Harm & Tragedy"
        "Drugs",
        "War & Conflict",
        "Politics"
        "Finance",
        "Legal"
      scores": [
       0.1.
       0.1.
       0.1.
       0.1.
       0.1.
       0.1,
      "blocked": false
    'content": "<>"
```



Get Ready

Let's clap for you!



- Congratulations
- You have put your best foot forward to start your Generative Al Journey!
- Good Luck!
- Keep Learning Every Day!



Do Not Forget

In28
Minutes

- Recommend the course to your friends!
 - Do not forget to review!
- Your Success = My Success
 - Share your success story with me on LinkedIn (Ranga Karanam)
 - Share your success story and lessons learnt in Q&A with other learners!



What next?



- Learn Other Cloud Platforms:
 - Gartner predicts a multi cloud world soon
 - Get certified on AWS, Azure and Google Cloud
- Learn DevOps (Containers and Container Orchestration)
- Learn Full Stack Development

