UNIT I

Two Stages of ML

The typical machine learning (ML) development process can be broken down into two primary stages:

1. Data Preparation and Model Training:

- o Data Collection and Preparation: Gathering relevant data, cleaning it, and transforming it into a suitable format for model training.
- o Model Selection and Training: Choosing an appropriate ML algorithm and training it on the prepared data to learn patterns.

2. Model Evaluation and Deployment:

- o Model Evaluation: Assessing the model's performance on a separate dataset to understand its accuracy and reliability.
- o Model Deployment: Integrating the trained model into a production environment to make predictions or decisions.

ML in Google Products

Google is a pioneer in applying ML to its products. Some prominent examples include:

- Search Engine: Understanding search queries, ranking results, and providing relevant information.
- Google Photos: Image recognition, object detection, and organization based on content.
- Google Translate: Real-time language translation using neural machine translation.
- Gmail: Spam filtering, smart reply, and priority inbox features.
- Google Assistant: Natural language understanding, speech recognition, and task completion.

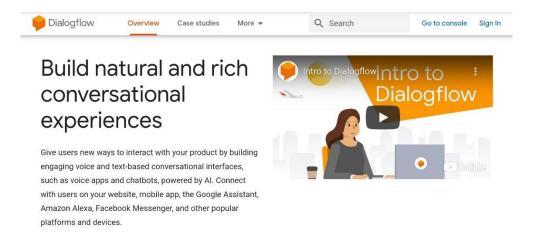
Dialogflow

Dialogflow (formerly known as Api.ai), is the platform owned by Google to build conversational agents.

Instead of building a chatbot from scratch, Dialogflow makes it easier to build it in considerably less time and with bunch of Google features, including pre-build ML Models that can help you get started right away. Dialogflow also allows you to integrate your conversational agent with popular platforms like Google Assistant, Facebook Messenger, Twitter, Telegram and more. It also provides Web API to integrate the agent into Websites.

Accessing Dialogflow Console:

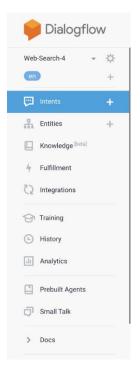
1) Visit https://dialogflow.com.



2) Sign-in using your Google Account and allow the access to Dialogflow.

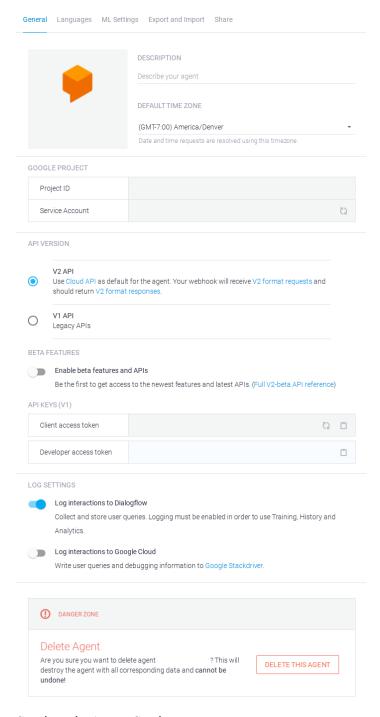


Getting familiar with Dialogflow Console:



Agents

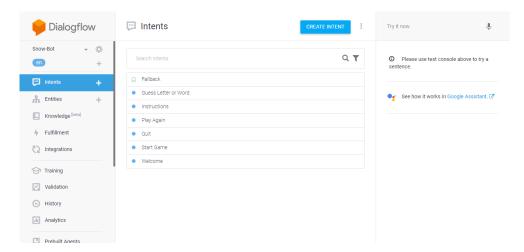
Every Conversational Chatbot you make using Dialogflow are called **Agents**. In the Console you can see all your agents in the top-left corner where you can configure the agent settings by clicking **Gear icon** next to your agent name.



Sections in Agent Settings:

- General: Here you can configure your Agent name, timezone and delete the agent.
- Export/Import: In this section you can backup and restore your Agents (It is good practice to Export your Agent periodically).

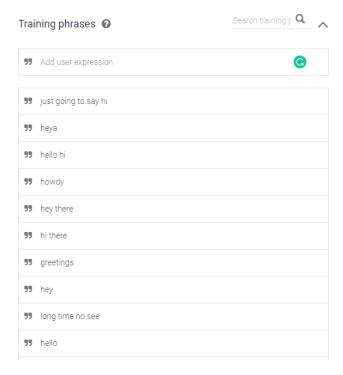
Intents



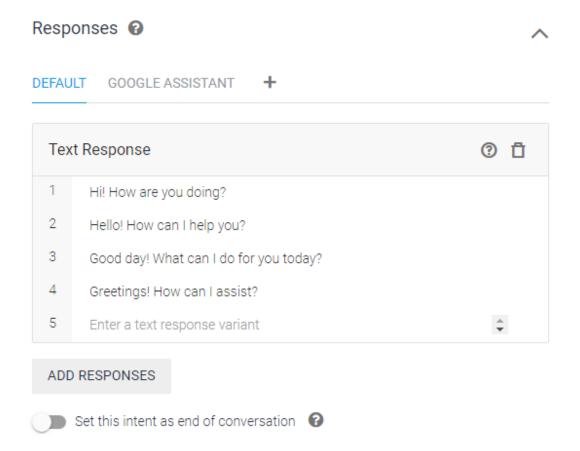
Intents comprises of what End-User's intend to say. For every agent, there are intents defined to fulfill End-User's query. Each intent has a specific purpose. When User types a query, Dialogflow matches the particular intent and responds to the User.

You can create an Intent using Create Intent button, or by using the Plus icon next to Intent in the Console Pane.

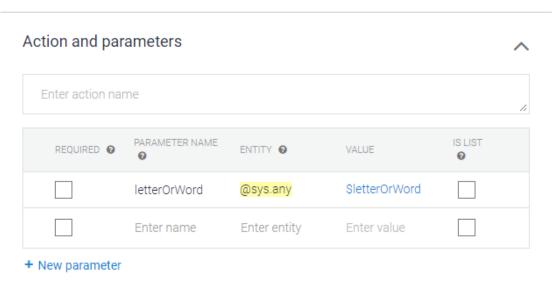
After opening an Intent, you enter the **Training Phrases**. These are the example phrases that User will say. When User's query resembles these phrases, Dialogflow will match the Intent. You need to define few phrases and the built-in Machine Learning will add more phrases over the time.



In the **Responses** section of Intent, you provide the statement which is used as the reply to the User's Invocation Phrase. You can define multiple replies and Dialogflow will randomly provide a reply from the given responses.



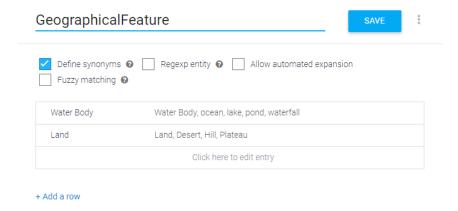
Other than Training Phrases and Responses, another powerful feature of Dialogflow is **Actions** and **Parameters**. In some intents you would like to obtain a particular data from User's phrase. You can define parameters by right-clicking any phrase from the Invocation Phrases list, and select the Entity-type that suits your requirement. Dialogflow has built-in parameters like *sys.geo-location*, *sys.date* and more. You can even define your own parameters (in the Entities).



Entities

Entities in context of Dialogflow are the set of Keywords that can be extracted as a parameter. You can define an Entity using **Create Entity** or the **Plus icon** next to Entity in the Console Pane.

Here, each Entry in the Entity holds a specific keyword. These keywords can have several synonyms. Dialogflow allows you to define synonyms along with the keyword.



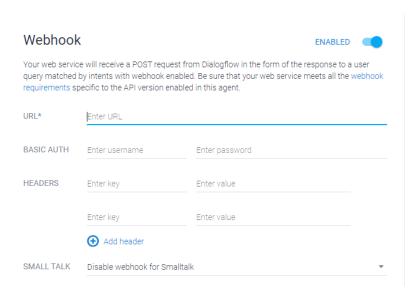
For example, if you define an entity "GeographicalFeature" with entry "Water Body" and define synonyms as *lake*, *pond*, *ocean*. When user says "I want to visit <u>ocean</u>". Dialogflow understands the reference and extracts the parameter as "Water Body".

Entities are really useful. These extracted parameters can be used to make conversations more human-like (using Fulfillment).

Fulfillment

Using **Fulfillment** adds more functionality to your agent. You have to enable Fulfillment for each Intent you require. There are two way to use the Fulfillment feature:

Webhook



Using Webhook, you can use externally deployed back-end to fulfill user query. The extracted parameter are packed using JSON. In the Webhook section you just need to provide the URL for your back-end and during each invocation, Dialogflow will send the user's query and Parameters to the back-end.

• Inline Editor

```
Inline Editor (Powered by Google Cloud Functions)

Build and manage fulfillment directly in Dialogflow via Cloud Functions. Docs

index.js package.json

firebase": {
    "projectId": "snow-bot-pqemem",
    "databaseURL": "https://snow-bot-pqemem.firebaseio.com",
    "storageBucket": "snow-bot-pqemem.appspot.com"
}
```

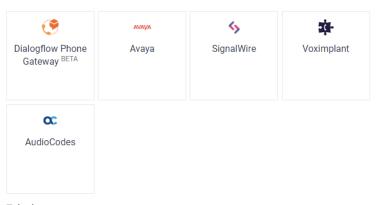
Inline Editor allows you to manage fulfillment directly from the cloud functions. You need to have understanding of NodeJS to use Inline Editor. Here you can modify **index.js** and **package.json** according to the requirement of your agent.

Integrations

After completing your agent, the last part is Integration. Here you can deploy your Agent to popular services like *Google Assistant*, *Facebook Messenger* and more. Select the platform to deploy your agent.



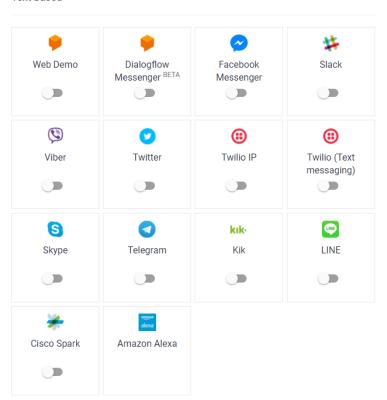
One-click telephony BETA



Telephony



Text based



Vision API

The Vision API is a powerful tool that uses machine learning to understand the content of images. It provides developers with a simple interface to access pre-trained models that can extract information from images.

How it works:

- 1. **Image Upload:** You send an image to the Vision API, either as an image file or an image URL.
- 2. **Image Analysis:** The API processes the image using advanced machine learning models.
- 3. **Response:** The API returns information about the image, such as labels, detected objects, or extracted text.

Key Features:

- Image Labeling: Identifies objects, places, and actions within an image.
- Face Detection: Detects faces within an image and provides information about attributes like emotions, landmarks, and poses.
- Optical Character Recognition (OCR): Extracts printed and handwritten text from images.
- Landmark Detection: Identifies famous landmarks within an image.
- Logo Detection: Recognizes logos of popular brands.
- Image Properties: Provides information about image properties like dominant colors.
- Safe Search Detection: Identifies potentially sensitive content within images.

Getting Started

- 1. Enable the Vision API: Visit the Google Cloud Platform console, navigate to the API & Services section, and enable the Vision API for your project.
- 2. Set Up Authentication: Create a service account with appropriate permissions and generate a key file.
- 3. Choose a Programming Language: The Vision API supports multiple languages, including Python, Java, Node.is, and Go.

1. Enabling the Google Cloud Vision API

To use the Google Cloud Vision API, you'll need to enable it for your Google Cloud project. Here's a step-by-step guide:

Prerequisites:

- A Google Cloud Platform (GCP) account.
- A Google Cloud project with billing enabled.

Steps:

- 1. **Sign in to the Google Cloud Console:** Visit https://console.cloud.google.com/ and sign in with your Google account.
- 2. **Select or Create a Project:** Choose an existing project or create a new one for your Vision API usage.

3. Enable the Vision API:

- o Navigate to the APIs & Services section in the console.
- o Search for "Cloud Vision API" and select it.
- o Click the **Enable** button.

2. Setting Up Authentication for the Google Cloud Vision API

To use the Google Cloud Vision API, you'll need to authenticate your requests. This ensures that Google can verify your identity and authorize access to the API.

Understanding Authentication Methods

There are two primary methods for authenticating with the Google Cloud Vision API:

- 1. **Application Default Credentials (ADC):** This method is suitable for local development and testing. It automatically uses the credentials associated with your Google account.
- 2. **Service Accounts:** For production environments and more granular control, service accounts provide a robust authentication mechanism.

Setting Up Service Accounts

1. Create a Service Account:

- o Go to the Google Cloud Console and navigate to the IAM & Admin section.
- Select "Service accounts" and click "Create Service Account".
- o Give your service account a name and description.
- o Grant the necessary roles to the service account. For Vision API, the "Cloud Vision API User" role is sufficient.

2. Create a Key:

- o Select the newly created service account and click the "Keys" tab.
- Click "Add Key" and choose "Create new key".
- Select the JSON key type and download the generated JSON file.

3. Store the Key:

Securely store the JSON key file. You'll use this file to authenticate your API requests.

3. How to Choose a Programming Language

Selecting the right programming language for a project can be a daunting task. Here are some key factors to consider:

Understand Your Project Requirements

- **Type of application:** Is it a web application, mobile app, desktop software, data analysis, or something else?
- **Platform:** Where will the application run (web, mobile, desktop, cloud)?
- **Performance requirements:** Are there specific speed or efficiency needs?
- Scalability: Will the application need to handle a large amount of data or users?
- **Security needs:** Are there sensitive data or security requirements?
- **Team expertise:** What languages are your team proficient in?

Evaluate Language Features

- Syntax and readability: How easy is the language to understand and maintain?
- Standard library: Does the language offer built-in functions for common tasks?
- Ecosystem: Is there a large and active community with libraries and frameworks?
- **Performance:** How fast is the language for different types of tasks?
- Cross-platform compatibility: Can the language be used for multiple platforms?
- Learning curve: How easy is it to learn the language?

Popular Languages and Their Use Cases

- **Python:** Versatile language for data science, machine learning, web development, and scripting.
- **JavaScript:** Primarily used for web development, but also gaining popularity in other areas.
- **Java:** Robust language for enterprise applications, Android app development, and big data processing.
- C++: High-performance language for system programming, game development, and performance-critical applications.
- C#: Used for Windows applications, game development, and web development with .NET.
- **Swift:** Apple's language for iOS app development.

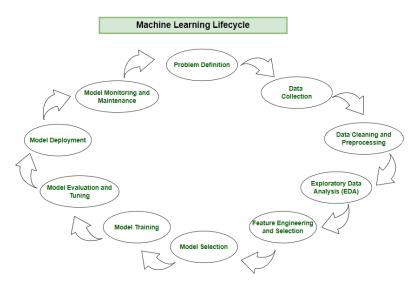
• Kotlin: Modern language for Android app development and multiplatform development.

ML training phases

The machine learning lifecycle is a process that guides the development and deployment of machine learning models in a structured way. It consists of various steps.

Each step plays a crucial role in ensuring the success and effectiveness of the machine learning solution. By following the machine learning lifecycle, organizations can solve complex problems systematically, leverage data-driven insights, and create scalable and sustainable machine learning solutions that deliver tangible value. The steps to be followed in the machine learning lifecycle are:

- 1. **Problem Definition**
- 2. Data Collection
- 3. Data Cleaning and Preprocessing
- 4. Exploratory Data Analysis (EDA)
- 5. Feature Engineering and Selection
- 6. Model Selection
- 7. Model Training
- 8. Model Evaluation and Tuning
- 9. Model Deployment
- 10. Model Monitoring and Maintenance



Machine Learning Lifecycle

Step 1: Problem Definition

Embarking on the machine learning journey involves a well-defined lifecycle, starting with the crucial step of problem definition. In this initial phase, stakeholders collaborate to identify the business problem at hand and frame it in a way that sets the stage for the entire process.

By framing the problem in a comprehensive manner, the team establishes a foundation for the entire machine learning lifecycle. Crucial elements, such as **project objectives**, **desired outcomes**, and the scope of the task, are carefully delineated during this stage.

Here are the basic features of problem definition:

- **Collaboration:** Work together with stakeholders to understand and define the business problem.
- Clarity: Clearly articulate the objectives, desired outcomes, and scope of the task.
- **Foundation:** Establish a solid foundation for the machine learning process by framing the problem comprehensively.

Step 2: Data Collection

Following the precision of problem definition, the machine learning lifecycle progresses to the pivotal stage of data collection. This phase involves the systematic gathering of datasets that will serve as the raw material for model development. The quality and diversity of the data collected directly impact the robustness and generalizability of the machine learning model.

During data collection, practitioners must consider the relevance of the data to the defined problem, ensuring that the selected datasets encompass the necessary features and characteristics. Additionally, factors such as data volume, quality, and ethical considerations play a crucial role in shaping the foundation for subsequent phases of the machine learning lifecycle. A meticulous and well-organized approach to data collection lays the groundwork for effective model training, evaluation, and deployment, ensuring that the resulting model is both accurate and applicable to real-world scenarios.

Here are the basic features of Data Collection:

- **Relevance:** Collect data that is relevant to the defined problem and includes necessary features.
- Quality: Ensure data quality by considering factors like accuracy, completeness, and ethical considerations.
- Quantity: Gather sufficient data volume to train a robust machine learning model.
- **Diversity:** Include diverse datasets to capture a broad range of scenarios and patterns.

Step 3: Data Cleaning and Preprocessing

With datasets in hand, the machine learning journey advances to the critical stages of data cleaning and preprocessing. Raw data, is often messy and unstructured. Data cleaning involves addressing issues such as missing values, outliers, and inconsistencies that could compromise the accuracy and reliability of the machine learning model.

Preprocessing takes this a step further by standardizing formats, scaling values, and encoding categorical variables, creating a consistent and well-organized dataset. The objective is to refine the raw data into a format that facilitates meaningful analysis during subsequent phases of the machine learning lifecycle. By investing time and effort in data cleaning and preprocessing, practitioners lay the foundation for robust model development, ensuring that the model is trained on high-quality, reliable data.

Here are the basic features of Data Cleaning and Preprocessing:

- **Data Cleaning:** Address issues such as missing values, outliers, and inconsistencies in the data.
- **Data Preprocessing:** Standardize formats, scale values, and encode categorical variables for consistency.
- **Data Quality:** Ensure that the data is well-organized and prepared for meaningful analysis.
- **Data Integrity:** Maintain the integrity of the dataset by cleaning and preprocessing it effectively.

Step 4: Exploratory Data Analysis (EDA)

Now, focus turns to understanding the underlying patterns and characteristics of the collected data. Exploratory Data Analysis (EDA) emerges as a pivotal phase, where practitioners leverage various statistical and visual tools to gain insights into the dataset's structure.

During EDA, patterns, trends, and potential challenges are unearthed, providing valuable context for subsequent decisions in the machine learning process. Visualizations, summary statistics, and correlation analyses offer a comprehensive view of the data, guiding practitioners toward informed choices in feature engineering, model selection, and other critical aspects. EDA acts as a compass, directing the machine learning journey by revealing the intricacies of the data and informing the development of effective and accurate predictive models.

Here are the basic features of Exploratory Data Analysis:

- **Exploration:** Use statistical and visual tools to explore the structure and patterns in the data.
- **Patterns and Trends:** Identify underlying patterns, trends, and potential challenges within the dataset.
- **Insights:** Gain valuable insights to inform decisions in later stages of the machine learning process.
- **Decision Making:** Use exploratory data analysis to make informed decisions about feature engineering and model selection.

Step 5: Feature Engineering and Selection

Feature engineering takes center stage as a transformative process that elevates raw data into meaningful predictors. Simultaneously, feature selection refines this pool of variables, identifying the most relevant ones to enhance model efficiency and effectiveness.

Feature engineering involves creating new features or transforming existing ones to better capture patterns and relationships within the data. This creative process requires domain expertise and a deep understanding of the problem at hand, ensuring that the engineered features contribute meaningfully to the predictive power of the model. On the other hand, feature selection focuses on identifying the subset of features that most significantly impact the model's performance. This dual approach seeks to strike a delicate balance, optimizing the feature set for predictive accuracy while minimizing computational complexity.

Here are the basic features of Feature Engineering and Selection:

- **Feature Engineering:** Create new features or transform existing ones to better capture patterns and relationships.
- **Feature Selection:** Identify the subset of features that most significantly impact the model's performance.
- **Domain Expertise:** Leverage domain knowledge to engineer features that contribute meaningfully to predictive <u>power.</u>
- Optimization: Balance feature set for predictive accuracy while minimizing computational complexity.

Step 6: Model Selection

Navigating the machine learning lifecycle requires the judicious selection of a model that aligns with the defined problem and the characteristics of the dataset. Model selection is a pivotal decision that determines the algorithmic framework guiding the predictive capabilities of the machine learning solution. The choice depends on the nature of the data, the complexity of the problem, and the desired outcomes.

Here are the basic features of Model Selection:

- **Alignment:** Select a model that aligns with the defined problem and characteristics of the dataset.
- **Complexity:** Consider the complexity of the problem and the nature of the data when choosing a model.
- **Decision Factors:** Evaluate factors like performance, interpretability, and scalability when selecting a model.
- **Experimentation:** Experiment with different models to find the best fit for the problem at hand.

Step 7: Model Training

With the selected model in place, the machine learning lifecycle advances to the transformative phase of model training. This process involves exposing the model to historical data, allowing it to learn patterns, relationships, and dependencies within the dataset.

Model training is an iterative and dynamic journey, where the algorithm adjusts its parameters to minimize errors and enhance predictive accuracy. During this phase, the model fine-tunes its understanding of the data, optimizing its ability to make meaningful predictions. Rigorous

validation processes ensure that the trained model generalizes well to new, unseen data, establishing a foundation for reliable predictions in real-world scenarios.

Here are the basic features of Model Training:

- **Training Data:** Expose the model to historical data to learn patterns, relationships, and dependencies.
- **Iterative Process:** Train the model iteratively, adjusting parameters to minimize errors and enhance accuracy.
- **Optimization:** Fine-tune the model's understanding of the data to optimize predictive capabilities.
- Validation: Rigorously validate the trained model to ensure generalization to new, unseen data.

Step 8: Model Evaluation and Tuning

Model evaluation involves rigorous testing against validation datasets, employing metrics such as accuracy, precision, recall, and F1 score to gauge its effectiveness.

Evaluation is a critical checkpoint, providing insights into the model's strengths and weaknesses. If the model falls short of desired performance levels, practitioners initiate model tuning—a process that involves adjusting hyperparameters to enhance predictive accuracy. This iterative cycle of evaluation and tuning is crucial for achieving the desired level of model robustness and reliability.

Here are the basic features of Model Evaluation and Tuning:

- Evaluation Metrics: Use metrics like accuracy, precision, recall, and F1 score to evaluate model performance.
- **Strengths and Weaknesses:** Identify the strengths and weaknesses of the model through rigorous testing.
- **Iterative Improvement:** Initiate model tuning to adjust hyperparameters and enhance predictive accuracy.
- **Model Robustness:** Iterate through evaluation and tuning cycles to achieve desired levels of model robustness and reliability.

Step 9: Model Deployment

Upon successful evaluation, the machine learning model transitions from development to real-world application through the deployment phase. Model deployment involves integrating the predictive solution into existing systems or processes, allowing stakeholders to leverage its insights for informed decision-making.

Model deployment marks the culmination of the machine learning lifecycle, transforming theoretical insights into practical solutions that drive tangible value for organizations.

Here are the basic features of Model Deployment:

- **Integration:** Integrate the trained model into existing systems or processes for realworld application.
- **Decision Making:** Use the model's predictions to inform decision-making and drive tangible value for organizations.
- **Practical Solutions:** Deploy the model to transform theoretical insights into practical solutions that address business needs.
- **Continuous Improvement:** Monitor model performance and make adjustments as necessary to maintain effectiveness over time.

AI Platform notebooks (Tour)

AI Platform Notebooks on Google Cloud provide an easy and powerful environment for data scientists to create and manage machine learning (ML) projects. Here's a simple explanation with examples:

Managed Jupyter Notebooks:

- **Explanation:** These notebooks are enhanced versions of standard Jupyter notebooks. Google Cloud manages the servers, so you don't have to worry about setting them up.
- **Example:** You can run Python code to analyze data or train a machine learning model using TensorFlow, without having to install anything on your computer. Just open your browser, and everything is ready for you.

Collaboration and Version Control:

- **Explanation:** AI Platform Notebooks integrate with Git, allowing you to track changes and collaborate with others easily.
- **Example:** If you make a mistake in your code, you can use Git to revert to an earlier version. You can also work on the same project with your team, seeing each other's changes in real time.

Customizable Hardware Profiles:

- **Explanation:** You can choose the type of hardware you need for your project, whether it's a powerful GPU for deep learning or just a CPU for data analysis.
- **Example:** If you're training a complex neural network, you might select a GPU to speed up the process. For simple tasks like data cleaning, you can stick with a basic CPU to save costs.

Integrated with Google Cloud Services:

- **Explanation:** The notebooks can connect to other Google Cloud services like BigQuery and Cloud Storage, making it easy to access and analyze large datasets.
- **Example:** You can query large datasets in BigQuery directly from your notebook and visualize the results with Matplotlib, all without leaving the notebook environment.

How to Get Started?

1. Create Your Notebook Instance:

- Explanation: Use the Google Cloud Console to set up a new notebook environment.
- **Example:** Choose a notebook template with TensorFlow pre-installed if you're planning to build a neural network.

2. Write Some Code:

- **Explanation:** Open your notebook and start coding. You can do everything from data preprocessing to model training and visualization.
- Example: Write Python code to load your dataset, train a machine learning model, and plot the results using libraries like Pandas and Matplotlib.

3. Collaborate and Share:

- Explanation: Share your notebook with colleagues to work together on the project.
- **Example:** Invite your team to review your code, discuss the results, and make improvements collaboratively.

4. Debugging and Exploration:

- **Explanation:** Use tools like the What-If Tool to understand how your model works and find any issues.
- **Example:** Visualize how changes in input data affect your model's predictions, helping you improve its accuracy.

Why Should You Care?

- **Productivity Boost:** No need to worry about installing software or dealing with dependencies. The environment is always ready for you.
- Scalability and Flexibility: Easily adjust the resources you need, scaling up or down as required by your project.
- **Data Science Nirvana:** Focus on analyzing data and building models, while Google Cloud takes care of the infrastructure. You can even deploy your models directly from the notebook.

Development process – Computations and Storage

The development process for AI Platform Notebooks involves several key stages, focusing on computations and storage. Here's a simple breakdown:

Development Process: Computations and Storage

1. Setting Up the Environment:

• Compute Resources:

- **Explanation:** Choose the appropriate hardware for your project needs, such as CPUs, GPUs, or TPUs.
- **Example:** For training a large deep learning model, you might opt for a GPU to accelerate computations.

• Storage Options:

- o **Explanation:** Decide on the storage capacity required for your data and models.
- Example: Use Google Cloud Storage for large datasets or to save model checkpoints during training.

2. Data Management:

• Data Ingestion:

- o **Explanation:** Import data from various sources into your notebook environment.
- **Example:** Load data from a CSV file stored in Google Cloud Storage or query a dataset from BigQuery.

• Data Preprocessing:

- o **Explanation:** Clean and prepare data for analysis and model training.
- o **Example:** Use Pandas to handle missing values and normalize data.

3. Model Development:

• Building Models:

- **Explanation:** Write and test code to create machine learning models using libraries like TensorFlow, PyTorch, or Scikit-learn.
- o **Example:** Develop a neural network for image classification using TensorFlow.

• Training Models:

- Explanation: Use the chosen compute resources to train models on your dataset.
- **Example:** Train a model on a GPU to reduce training time for a complex neural network.

• Hyperparameter Tuning:

- o **Explanation:** Optimize model performance by adjusting hyperparameters.
- **Example:** Use grid search or random search to find the best combination of learning rate and batch size.

4. Evaluation and Debugging:

• Model Evaluation:

- o **Explanation:** Assess model performance using appropriate metrics and validation data.
- o **Example:** Calculate accuracy, precision, and recall for a classification model.

• Debugging:

- o **Explanation:** Identify and fix issues in your code or model.
- **Example:** Use the What-If Tool to analyze model predictions and understand errors.

5. Collaboration and Version Control:

• Collaboration:

- o **Explanation:** Work with team members to improve and refine models.
- **Example:** Share notebooks via Google Cloud and use comments to discuss code changes.

• Version Control:

- o **Explanation:** Use Git to track changes and maintain versions of your notebook.
- o **Example:** Revert to a previous version if a recent change caused an issue.

6. Deployment:

• Model Deployment:

- o **Explanation:** Transition models from development to production environments.
- Example: Deploy a trained model using AI Platform Predictions to serve predictions via an API.

• Monitoring:

- o **Explanation:** Continuously monitor model performance in production.
- Example: Set up alerts to track model accuracy and latency.