

Machine Learning Engineer Learning Path

mardi 13 juin 2023 15:28

Google Cloud Big Data and Machine Learning Fundamentals

Big data and Machine learning on Google Cloud

Google Cloud infrastructure: 3 layers: 1) Networking & security, 2) compute, storage, 3) Big data ML products

Compute:

compute power:

- Compute Engine: is an IaaS offering, or infrastructure as a service, which provides compute, storage, and Network resources virtually that are similar to physical data centers.
- Google Kubernetes Engine, or GKE: runs containerized applications in a cloud environment, as opposed to on an individual virtual machine, like Compute Engine. (consider dependencies.)
- App Engine, a fully managed PaaS offering, or platform as a service: PaaS offerings bind code to libraries. serverless execution environment. Cloud Functions is often used for event-driven workloads.
- Cloud Run: a fully managed compute platform that enables you to run request or event-driven stateless workloads without having to worry about servers. It automates the scaling and management of containers.

Google Photos: automatic video stabilization: takes an unstable video, stabilizes it to minimize movement.

TPU introduced by Google 2016 to overcome CPU and GPU. TPU is application-specific integrated circuits (ASICs). domain-specific hardware

Storage

Cloud (compute-storage decoupled) vs desktop (compute-storage coupled) computing

fully managed database and storage services: Cloud Storage, Cloud Bigtable, Cloud SQL, Cloud Spanner, Firestore And BigQuery

Goal=reduce the time and effort needed to store data (creating an elastic storage bucket directly in a web interface or through a command line for example on Cloud Storage). Storage depends on data type, and business need.

(un)Structured data = (non)tabular

Unstructured suited to Cloud Storage (also BigQuery),

An object is an immutable piece of data consisting of a file of any format. You store objects in containers called buckets. All buckets are associated with a project, and you can create as many buckets as you need. Each project, bucket, and object in Google Cloud is a resource in Google Cloud,

Cloud Storage classes (suited for unstructured data):

- Standard (best for frequently accessed, or hot data. stored for only brief periods of time)
- Nearline (infrequently accessed data: data backups, long-tail multimedia content, or data archiving.)
- Coldline (low-cost option for storing infrequently accessed data. once every 90 days)
- Archive (lowest-cost option, used ideally for data archiving, online backup, and disaster recovery. access less than once a year.)

Structured data:

- transactional workloads (stem from Online Transaction Processing systems, which are used when fast data inserts and updates are required to build row-based records that impact only a few records.)
- and analytical workloads (stem from Online Analytical Processing systems, which are used when entire datasets need to be read. require complex queries, for example, to calculate averages or totals across the dataset.)

Then determine whether data will be accessed using SQL or not:

- Transactional-SQL-local/regional scalability-Cloud SQL
- Transactional-SQL-global scalability-Cloud Spanner
- Transactional-NoSQL-Firestore
- Analytical-SQL-BigQuery (analyze petabyte-scale datasets)
- Analytical-NoSQL-Cloud Bigtable (best for real-time, high-throughput applications that require only milliseconds)

Big data:

- 2002: Google File System, GFS, was designed to handle data sharing and petabyte storage at scale.
 - 2004: MapReduce
 - 2008: Dremel: breaking the data into smaller chunks called shards, and then compressing them. then uses a query optimizer to share tasks between the many shards of data.
 - 2010: Colossus, in 2010, which is a cluster-level file system and successor to the Google File System. It is a Platform as a Service (PaaS) that supports querying using ANSI SQL.
 - 2012: Spanner, in 2012, which is a globally available and scalable relational database.
 - 2015: Pub/Sub, in 2015, which is a service used for streaming analytics and data integration pipelines to ingest and distribute data.
 - 2015: TensorFlow, also in 2015, which is a free and open source software library for machine learning and artificial intelligence.
 - 2018: brought the release of the Tensor Processing Unit, or TPU, and AutoML, as a suite of machine learning products.
 - 2021: Vertex AI, a unified ML platform
- Unified and stable platform: Cloud Storage Dataproc Cloud Bigtable BigQuery Dataflow Firestore Pub/Sub Looker Cloud Spanner AutoML, and Vertex AI,

Product categories along the data-to-AI workflow:

- ingestion & process: to digest both real-time and batch data (Pub/Sub, Dataflow (streaming data processing), Dataproc, Cloud Data Fusion)
 - storage: (Cloud Storage, Cloud SQL (relational), Cloud Spanner (relational), Cloud Bigtable (NoSQL), and Firestore (NoSQL))
 - analytics: (BigQuery: a fully managed data warehouse that can be used to analyze data through SQL commands; Looker, and Looker Studio)
 - ML: ML development platform and the AI solutions. (Vertex AI which includes the products and technologies: AutoML, Vertex AI Workbench, and TensorFlow)
- AI solutions are built on the ML development platform and include state-of-the-art products to meet both horizontal and vertical market needs: Document AI, Cloud Healthcare Data Engine

Example:

- A unicorn is a privately held startup business valued at over US\$1 billion.
- For data latency: Dataflow (streaming data processing) + BigQuery (real-time business insights)
- For geospatial: Dataflow (a streaming event data pipeline).
 - driver locations ping Pub/Sub every 30 seconds, and
 - Dataflow would process the data (was able to automatically manage the number of workers processing the pipeline to meet demand)
 - The pipeline would aggregate the supply pings from the drivers against the booking requests.
 - This would connect to Gojek's notification system to alert drivers where they should go
- Conclusion: actively monitor requests to ensure that drivers are in the areas with the highest demand. This brings faster bookings for riders and more work for the drivers.

Data Engineering for streaming data

real-time data solution:

Ingest streaming data using Pub/Sub (data ingestion is where large amounts of streaming data are received)

Process the data with Dataflow, and

Visualize the results with Looker and Looker Studio

(In between data processing with Dataflow and visualization with Looker or Looker Studio, the data is normally saved and analyzed in a data warehouse such as BigQuery)

design streaming pipelines with Apache Beam

streaming vs batch processing (media streaming vs downloading):

Batch processing is when the processing and analysis happens on a set of stored data: Payroll and billing systems

Streaming data is a flow of data records generated by various data sources: fraud detection or intrusion detection. data is analyzed in near real-time

4Vs: data engineers and data scientists four major challenges = variety, volume, velocity, and veracity:

data could come in from a variety of different sources and in various formats

Veracity: data quality (Due to several data types and sources, big data often has many data dimensions)

IoT devices challenge:

data can be streamed from many different methods and devices

it can be hard to distribute event messages (notification) to the right subscribers

data can arrive quickly and at high volumes.

ensuring services are reliable, secure, and perform as expected

Pub/Sub:

a tool to handle distributed message-oriented architectures at scale

(Publisher/Subscriber, or publish messages to subscribers).

distributed messaging service

Pub/Sub's APIs are open, the service is global by default, and it offers end-to-end encryption

end-to-end encryption:

Pub/Sub reads, stores, broadcasts to any subscribers of this data topic that new messages are available

A central element of Pub/Sub is the topic.

Designing streaming pipelines with Apache Beam:

streaming input sources + pipe data into a data warehouse (dataflow)

"Process" : extract, transform, and load data, or ETL.

pipeline design phase questions:

Will the pipeline code be compatible with both batch and streaming data? Or need to be refactored?

Will the pipeline code software development kit, or SDK, being used have all the transformations, mid-flight aggregations and windowing and be able to handle late data?

Are there existing templates or solutions that should be referenced?

pipeline design: Apache Beam: an open source, unified programming model to define and **execute data processing pipelines**, including ETL, batch, and stream processing

unified, which means it uses a single programming model for both batch and streaming data

It's portable, which means it can work on multiple execution environments, like Dataflow and Apache Spark

extensible, which means it allows you to write and share your own connectors and transformation libraries.

Apache Beam provides pipeline templates (Java, Python, or Go)

Implementing streaming pipelines on Cloud Dataflow:

Questions:

How much maintenance overhead is involved?

Is the infrastructure reliable?

How is the pipeline scaling handled?

How can the pipeline be monitored?

Is the pipeline locked in to a specific service provider?

Dataflow is a fully managed service for executing Apache Beam pipelines within the Google Cloud

Dataflow is serverless and NoOps

NoOps: doesn't require management from an operations team, because maintenance, monitoring, and scaling are automated.

Serverless computing is a cloud computing execution model

Dataflow tasks :

optimizing a pipeline model's execution graph

schedules out distributed work

scaler

auto-heals any worker faults

rebalances efforts to most efficiently use its workers.

execution engine to process and implement data processing pipelines

you don't need to monitor all of the compute and storage resources that Dataflow manages,

Dataflow templates:

streaming templates (for processing continuous, or real-time, data): Pub/Sub to BigQuery, Pub/Sub to Cloud Storage, Datastream to BigQuery, Pub/Sub to N

batch templates (for processing bulk data, or batch load data.): BigQuery to Cloud Storage, Bigtable to Cloud Storage, Cloud Storage to BigQuery, Cloud Spar

utility templates (activities related to bulk compression, deletion, and conversion)

Visualization with Looker:

Looker: semantic modeling layer on top of databases using Looker Modeling Language, or LookML

LookML defines logic and permissions independent from a specific database or a SQL language,

The Looker platform is 100% web-based, which makes it easy to integrate into existing workflows and share with multiple teams at an organization

Looker API, which can be used to embed Looker reports in other applications.

Looker features:

Dashboards: schedule its delivery through storage services like: Google Drive, Slack, Dropbox.

Visualization with Data Studio:

Looker Studio: integrated into BigQuery: doesn't require support from an administrator to establish a data connection, which is a requirement with Looker

integrated into Google Analytics, Google Cloud billing dashboard

to create a Looker Studio dashboard:

choose a template (a pre-built template or a blank report)

link the dashboard to a data source.

Lab introduction: Creating a streaming data pipeline for a Real-Time dashboard with Dataflow:

gcloud is the command-line tool for Google Cloud.

pre-installed on Cloud Shell and supports tab-completion

list the active account name: gcloud auth list

list the project ID: gcloud config list project

to create dataset: Google Cloud Shell or the Google Cloud Console.

[Pub/Sub](#) is an asynchronous global messaging service.

decoupling senders and receivers, it allows for secure and highly available communication between independently written applications delivers low-latency, durable messaging publisher applications and subscriber applications connect with one another through the use of a shared string called a **topic** Google maintains a few public Pub/Sub streaming data topics

[BigQuery](#) is a serverless data warehouse

Tables in BigQuery are organized into datasets.

to create a new BigQuery dataset:

command-line tool (**Cloud Shell**):

Create dataset: bq --location=us-west1 mk taxirides

Create Table: bq --location=us-west1 mk \

--time_partitioning_field timestamp \

--schema ride_id:string,point_idx:integer,latitude:float,longitude:float,\

timestamp:timestamp,meter_reading:float,meter_increment:float,ride_status:string,\

passenger_count:integer -t taxirides.realtime

BigQuery Console UI:

Create a Cloud Storage bucket (to provide working space for your Dataflow pipeline)

[Cloud Storage](#) allows world-wide storage and retrieval of any amount of data at any time

Applications: serving website content, storing data for archival and disaster recovery, or distributing large data objects to users via direct download.

Set up a Dataflow Pipeline

set up a streaming data pipeline to read sensor data from Pub/Sub, compute the maximum temperature within a time window, and write this out to B

Restart the connection to the Dataflow API.

Create a new streaming pipeline

Analyze the taxi data using BigQuery:

SELECT * FROM taxirides.realtime LIMIT 10

Perform aggregations on the stream for reporting

Stop the Dataflow Job (to free up resources for your project)

Create a real-time dashboard

Create a time series dashboard

Summary:

used Pub/Sub to collect streaming data messages from taxis and feed it through your Dataflow pipeline into BigQuery

Pub/Sub, which can be used to ingest a large volume of IoT data from diverse resources in various formats.

Dataflow, a serverless, NoOps service, to process the data. 'Process' here refers to ETL (extract, transform, and load).

Big data with BigQuery:

BigQuery's two main services, storage and analytics

BigQuery is a fully managed data warehouse

A data warehouse is a large store, containing terabytes and petabytes of data gathered from a wide range of sources within an organization, that's used to g

A **data lake** is just a pool of **raw, unorganized, and unclassified** data, which has **no specified purpose**. A data warehouse on the other hand, contains structu used for **advanced querying**

Being **fully managed** means that BigQuery **takes care of the underlying infrastructure**, so you can focus on using SQL queries to answer business questions, scalability, and security.

BigQuery Storage: to store petabytes of data. **1 petabyte** is equivalent to **11,000 movies at 4k** quality.

BigQuery analytics: **machine learning** (using SQL), **geospatial analysis**, and **business intelligence**,

BigQuery is a fully managed serverless solution, meaning that you don't need to worry about provisioning any resources or managing servers in the backend to answer your organization's questions in the frontend.

By **encryption at rest**, we mean encryption used to protect data that is stored on a **disk**, including solid-state drives, or backup media.

data warehouse solution architecture:

input data can be either real-time or batch data

streaming data, which can be either structured or unstructured, high speed, and large volume, Pub/Sub is needed to digest the data.

If it's batch data, it can be directly uploaded to Cloud Storage.

both pipelines (real-time or batch data) lead to Dataflow to process the data (ETL)

(real-time+Pub/Sub)(batch data+Cloud Storage)+Dataflow (ETL)+BigQuery(analytics,AI, and ML)+(business intelligence(BI) tools)(AI/ML tools)

The job of the analytics engine of BigQuery at the end of a data pipeline is to ingest all the processed data after ETL, store and analyze it, and possibly c visualization and machine learning.

business analyst, BI developers: If you prefer to work in spreadsheets, you can query both small or large BigQuery datasets directly from **Google Sheet** operations like pivot tables.

data scientist or machine learning engineer: you can directly call the data from BigQuery through **AutoML** or **Workbench** (parts of Vertex AI)

BigQuery is like a common staging area for data analytics workloads

Storage and analytics

BigQuery :**fully managed storage facility to load and store datasets**, and also a **fast SQL-based analytical engine**

The two services are connected by **Google's high-speed internal network**.

BigQuery can ingest datasets from : **internal** data(data saved directly in BigQuery), **external** data, **multi-cloud** data (data stored in **multiple cloud services**, s datasets.

After the data is stored in BigQuery, it's fully managed by BigQuery and is **automatically replicated, backed up, and set up to autoscale**

BigQuery also offers the option to **query external data sources**—like data stored in other **Google Cloud storage** services like **Cloud Storage**, or in other **Googl** **Spanner** or **Cloud SQL**

That means a raw CSV file in Cloud Storage or a Google Sheet can be used to write a query **without being ingested by BigQuery first**

inconsistency might result from **saving and processing data separately**. To avoid that risk, consider using **Dataflow** to build a **streaming data pipeline** into l patterns to load data into BigQuery:

batch load, where source data is loaded into a BigQuery table in a single batch operation. (**one-time** operation or it can be **automated to occur on a sc**

A batch load operation can create a **new** table or **append** data into an existing table.

streaming, where **smaller batches of data are streamed continuously** so that the data is available for **querying in near-real time**

generated data, where SQL statements are used to insert rows into an existing table or to write the results of a query to a table.

BigQuery is optimized for running analytic queries over large datasets.

It can perform queries on **terabytes of data in seconds and on petabytes in minutes**.

BigQuery analytics features:

Ad hoc analysis using Standard SQL, the **BigQuery SQL** dialect.

Geospatial analytics using geography data types and Standard SQL geography functions.

Building **machine learning models** using **BigQuery ML**.

Building rich, interactive **business intelligence dashboards** using **BigQuery BI Engine**.

Query types:

BigQuery runs **interactive** queries, which means that the **queries are executed as needed**

batch queries, where **each query is queued** on your behalf and the query starts **when idle resources are available**, usually within a few minutes.

BigQuery demo - San Francisco bike share

- o If **no hyphen** in the project name, no need to **back ticks** around the project name
- o hold down the command key or the **Windows** key it'll highlight all the data sets in your query, so you can click on it
- o Click on Query Table. Click on field names from Schema to add them into Query editor (no need to write names)
- o More>Format
- o Run

SELECT, FROM, AS, GROUP BY, ORDER BY, WHERE, DESC, LIMIT

Explore In Data Studio

data definition language (DDL): I want a creation statement inside of the actual code itself

Create dataset

CREATE OR REPLACE **TABLE** <dataset name>.<table name> AS

CREATE OR REPLACE **VIEW** <dataset name>.<view name> AS : If the original public dataset updates, the derived table will update

Introduction to BigQuery ML:

Traditional:

export data from **datastore** into an **IDE** (integrated development environment) such as **Jupyter Notebook** or **Google Colab**

transform the data and perform all your **feature engineering** steps **before you can feed it into a training model**.

build the model in TensorFlow, or a similar library, and train it **locally** on your computer or on a **virtual machine**.

To **improve the model performance**, you also need to go back and forth to **get more data and create new features**.

BigQuery:

- **Create a model** with a SQL statement
- Write a **SQL prediction query** and invoke ml.Predict
- evaluating the model,

Hyperparameters are the settings applied to a model **before the training starts**, like the learning rate

Choosing which type of ML model depends on your **business goal and the datasets**.

Supervised models are **task-driven and identify a goal**.

Goal: classification: logistic regression

goal :predict a number (regression): linear regression

unsupervised models are **data-driven and identify a pattern**

goal: identify patterns or clusters: cluster analysis

We recommend that you start with these options (logistic/linear regression), and use the results to **benchmark** to compare against more complex networks(XGBoost,AutoML Tables, wide and deep DNNs), which may take more time and computing resources to train and deploy

machine learning operations (ML Ops): BigQuery ML supports features to **deploy, monitor, and manage the ML production**

Importing TensorFlow models for batch prediction

Exporting models from BigQuery ML for online prediction

hyperparameter tuning using **Vertex AI Vizier**

ML development: upload data, engineer feature, train model, evaluate result

Using BigQuery ML to predict customer lifetime value (LTV):

LTV: to estimate how much revenue or profit you can expect from a customer given their history and customers with similar patterns.

a **record or row** in the dataset is called an **example, an observation, or an instance**.

A **label** is a correct answer, and you know it's correct because it comes from historical data.

Depending on what you want to predict, a label can be either a **numeric** variable, which requires a **linear regression** model, or a **categorical** variable, w model.

Those columns are called **features**, or at least potential features.

Understanding the quality of the data in each column and working with teams to **get more features or more history** is often the hardest part of any ML pro

feature engineering: **combine or transform feature** columns

BigQuery ML **automatically does one-hot encoding** for categorical values.

BigQuery ML **automatically splits the dataset into training data and evaluation data**

BigQuery ML project phases:

phase 1: **you extract, transform, and load** data into BigQuery, if it isn't there already.

If you're already using other Google products, like YouTube for example, look out for easy **connectors** to get that data into BigQuery before you build y

You can **enrich your existing data warehouse with other data sources** by using **SQL joins**.

phase 2: you **select** and **preprocess** features.

You can use **SQL** to create the training dataset for the model to learn from

phase 3: **you create the model inside BigQuery**.

This is done by using the **"CREATE MODEL"** command.

Give it a **name**, specify the **model type**, and pass in a SQL query with your training dataset.

phase 4: **after your model is trained**, you can execute an **ML.EVALUATE** query to **evaluate** the performance of the trained model on your evaluation dataset.

phase 5: use it to **make predictions**.

invoke the **ml.PREDICT** command on your newly trained model to return with predictions and the model's confidence in those predictions.

BigQuery ML key commands:

CREATE MODEL: create a model. Models have **OPTIONS** (model type), which you can specify.

CREATE OR REPLACE MODEL: to overwrite an existing model

ML.WEIGHTS: inspect what a model learned

That value indicates **how important the feature is for predicting the result**, or label.

ML.EVALUATE: To evaluate the model's performance

ML.PREDICT: to make batch predictions

BigQuery ML commands for supervised models:

Labels: you need a field in your training dataset titled **LABEL**, or you need to specify which field or fields are your labels using the **input_label_cols** in y

Feature: features are the data columns that are part of your **SELECT** statement after your **CREATE MODEL** statement.

After a model is trained, you can use the **ML.FEATURE_INFO** command to get **statistics and metrics** about that column for additional analysis.

model object: created in BigQuery that **resides in your BigQuery dataset**. You train many different models, which will all be objects stored under your **tables and views**. Model objects can display information for **when it was last updated** or **how many training runs** it completed

Model types (regression/classification): Creating a new model is as easy as writing CREATE MODEL, choosing a type, and passing in a training dataset.

Training progress: While the model is running, and even after it's complete, you can view training progress with **ML.TRAINING_INFO**.

inspect weights (ML.WEIGHTS): to see what the model learned about the importance of each feature as it relates to the label you're predicting.

ML.EVALUATE: how well the model performed against its evaluation dataset.

ML.PREDICT: getting predictions (through referencing your model name and prediction dataset)

Predicting Visitor Purchases with a Classification Model with BigQuery ML:

BQML: a feature in BigQuery where data analysts can **create, train, evaluate, and predict** with machine learning models with **minimal coding**

Create a BigQuery dataset to store models

the web analytics dataset has nested and repeated fields like **ARRAYS** which **need to be broken apart into separate rows** in your dataset. This is accomplished

Machine learning options on google cloud:

Smart Reply: Gmail automatically suggests three responses to a received message. it uses artificial intelligence (natural language processing) to predict how you might respond. The goal is to enable every company to be an AI company by **reducing the challenges of AI model creation** to only the steps that require **human judgment or creativity**.

Options to build ML models:

- BigQuery ML**: uses SQL queries to create and execute machine learning models in BigQuery
- pre-built APIs**: lets you **leverage machine learning models that have already been built and trained by Google**, so you don't have to build your own machine learning models. Requires enough training data or sufficient machine learning expertise in-house.
- AutoML**: is a **no-code solution**, so you can **build your own machine learning models** on **Vertex AI** through a **point-and-click interface**.
- custom training**: through which you can **code your very own machine learning environment, the training, and the deployment**, which gives you flexibility a pipeline.

Differences between options:

Data type: BigQuery ML only supports tabular data while the other three support tabular, image, text, and video

Training data size: Pre-built APIs do not require any training data, while BigQuery ML and custom training require a large amount of data

Machine learning and coding expertise: Pre-Built APIs and AutoML are user friendly with low requirements, while Custom training has the highest requirement for you to understand SQL.

Flexibility to tune the hyperparameters: At the moment, you can't tune the hyperparameters with Pre-built APIs or AutoML, however, you can experiment with BigQueryML and custom training.

Time to train the model: Pre-built APIs require no time to train a model because they directly use pre-built models from Google. The time to train a model with custom training depends on the specific project.

Normally, custom training takes the longest time because it builds the ML model from scratch, unlike AutoML and BigQuery ML.

Which option:

- BigQuery ML**: data engineers, data scientists, and data analysts are familiar with SQL and already have your data in BigQuery: **BigQuery ML** lets you develop models with SQL.
- pre-built APIs**: business users or developers with little ML experience: pre-built APIs (vision, video, and natural language)
- AutoML**: If your developers and data scientists want to **build custom models** with your **own training data** while spending **minimal time coding**, then AutoML provides a code-less solution to enable you to focus on business problems instead of the underlying model architecture and ML provisioning.
- custom training**: If your ML engineers and data scientists want **full control of ML workflow**, **Vertex AI** custom training lets you train and serve custom models.

Pre-built APIs:

Good Machine Learning models require **lots of high-quality training data**. You should aim for **hundreds of thousands** of records to train a custom model. If you don't have enough data, pre-built APIs are a great place to start.

Pre-built APIs are offered as services.

They save the time and effort of **building, curating, and training** a new dataset so you can just jump right ahead to predictions

API examples:

The Speech-to-Text API: converts audio to text for data processing.

The Cloud Natural Language API: recognizes **parts of speech** called entities and sentiment.

The Cloud Translation API: converts text from one language to another.

The Text-to-Speech API: converts text into high quality voice audio.

The Vision API: works with and recognizes **content** in static images.

cloud.google.com/vision

The Video Intelligence API: recognizes **motion and action** in video.

You can actually **experiment** with each of the ML APIs in a **browser**.

When you're ready to **build a production model**, you'll need to **pass a JSON object request to the API and parse what it returns**.

AutoML:

training and deploying ML models can be extremely time consuming, because to achieve the best result you need to repeatedly add new data and features, try different models, and tune parameters.

AutoML was first announced in January of 2018, the goal was to **automate machine learning pipelines** to **save data scientists from manual work**

For AutoML, two technologies are vital:

- transfer learning**: is a powerful technique that lets people with **smaller datasets, or less computational power**, achieve state-of-the-art results by taking models that have been trained on **similar, larger data sets**. Because the model learns via transfer learning, it **doesn't have to learn from scratch**, so it can generally reach higher accuracy with much less data than if it had to learn from scratch.
- neural architecture search**: to find the **optimal model** for the relevant project.

AutoML platform actually trains and evaluates **multiple models** and compares them to each other

This neural architecture search produces an **ensemble of ML models** and chooses the best one.

It is a **no-code solution**: minimal effort and requires little machine learning expertise

AutoML is a tool to **quickly prototype models** and explore new datasets before investing in development.

How AutoML works:

For each data type (image, tabular, text, and video), AutoML solves different types of problems, called **objectives**.

upload your data (from Cloud Storage, BigQuery, or even your local machine) into AutoML.

AutoML will then **inform** AutoML of the problems you want to solve.

Some problems may sound similar to those mentioned in pre-built APIs. However the major difference is that pre-built APIs use **pre-built machine learning models**.

In AutoML, you use your **own data** to train the machine learning model.

Objectives:

1. Classification

- For image data:
 - You can use a **classification model** to analyze image data and return a list of **content categories** that apply to the image.
 - You can also use an **object detection model** to analyze your image data and return **annotations** that consist of a **label** and **bounding box** on an image.
- For tabular data:
 - You can use a **regression model** to analyze tabular data and return a numeric value.
 - You can use a **classification model** to analyze tabular data and return a list of categories.
 - And a **forecasting model** can use multiple rows of **time-dependent** tabular data from the past to predict a series of numeric values in the future.
- For text data:
 - You can use a **classification model** to analyze text data and return a list of categories that apply to the text found in the data.
 - An **entity extraction model** can be used to inspect text data for known entities referenced in the data and label those entities in the text (e.g., **hashtag**, but created by machine).
 - A **sentiment analysis model** can be used to inspect text data and identify the prevailing emotional opinion within it, especially to determine if it is positive, negative, or neutral.
- For video data:
 - You can use a **classification model** to analyze video data and return a list of **categorized shots and segments**.
 - You can use an **object tracking model** to analyze video data and return a list of **shots and segments where these objects were detected**.
 - And an **action recognition model** can be used to analyze video data and return a **list of categorized actions with the moments the actions occurred**.

Custom training

Using Vertex AI Workbench

Workbench is a **single development environment for the entire data science workflow**, from exploring, to training, and then deploying a machine learning model. You can use a **pre-built container** (includes dependencies and libraries) or a **custom container** (empty: no libraries).

Vertex AI

Some traditional challenges

determining how to handle **large quantities of data**,
 Determining the **right machine learning model** to train the data,
 harnessing the required amount of **computing power**.

Production challenges:

scalability,
 monitoring,
 continuous integration and continuous delivery or deployment

ease-of-use challenges.

Many tools on the market require advanced coding skills,
 which can take a data scientist's focus away from model configuration.
 no unified workflow.

Google's solution to the above challenges: Vertex AI: a **unified platform** that brings all the components of the **machine learning ecosystem and workflow** to a single place. Vertex AI, a tool that **combines the functionality of AutoML**, which is codeless, and **custom training**, which is code-based, **to solve production and ease-of-use challenges**.

unified platform: one digital experience to **create, deploy, and manage** models **over time, and at scale**:

1. **data readiness stage**: users can **upload** data from wherever it's stored— **Cloud Storage, BigQuery, or a local machine**.
2. **during the feature readiness stage**: users can **create features**, which are the **processed data** that will be put into the model, and then share them.
3. **Training and Hyperparameter tuning**. This means that when the data is ready, users can **experiment** with different models and **adjust hyperparameters**.
4. **deployment and model monitoring**: users can set up the pipeline to **transform the model into production** by **automatically monitoring** and performing updates.

Vertex AI allows users to **build** machine learning models with either **AutoML**, or **Custom Training**.

AutoML is easy to use and lets data scientists spend more time **turning business problems into ML solutions**, while custom training enables data scientists to **customize the development environment and process**.

Vertex AI properties:

seamless: Vertex AI provides a **smooth** user experience from **uploading and preparing data all the way to model training and production**.

Scalable: The Machine Learning Operations (**MLOps**) provided by Vertex AI helps to **monitor and manage** the ML **production** and therefore **scale the service** automatically.

sustainable. All of the artifacts and features created using Vertex AI can be **reused and shared**.

speedy: Vertex AI produces models that have **80% fewer lines of code** than competitors.

AI Solutions:

Google Cloud's artificial intelligence solution portfolio (three layers):

the AI foundation: Google Cloud infrastructure (compute, storage, networking) and data (BQ, Dataflow, Looker).

the AI development platform: AutoML and custom training, which are offered through Vertex AI, and pre-built APIs and BigQuery ML.

AI solutions:

horizontal solutions:

usually apply to any industry that would like to solve the same problem.

Document AI and CCAI

Document AI uses **computer vision** and **optical character recognition**, along with **natural language processing**, to create pretrained models for processing documents.

The goal is to **increase the speed and accuracy** of document processing to help organizations make better decisions faster, while **reducing costs**. Contact Center AI, or CCAI. The goal of CCAI is to improve **customer service** in contact centers through the use of artificial intelligence.

It can help **automate simple interactions, assist human agents, unlock caller insights, and provide information to answer customer questions**.

vertical/industry solutions:

relevant to specific industries.

Retail Product Discovery, which gives retailers the ability to provide **Google-quality search and recommendations on their own digital products** conversions and reduce search abandonment.

Healthcare Data Engine, which generates **healthcare insights and analytics** with one **end-to-end solution**.

Lending DocAI, which aims to transform the **home loan** experience for borrowers and lenders by **automating mortgage document processing**.
cloud.google.com/solutions/ai

Summary

The machine learning **Workflow** with **Vertex AI**:

Introduction:

basic differences between machine learning and traditional programming:

Traditional: Data, plus rules—otherwise known as algorithms—lead to answers: **Data+rules(algorithms)=answers**

computer can only follow the algorithms that a human has set up

ML: the algorithms are too complex to figure out

we feed a machine a **large amount of data, along with answers** that we would expect a model to conclude from that data

For machine learning to be successful:

- lots of storage**, like what's available with **Cloud Storage**,
- the ability to make **fast calculations**, like with **cloud computing**.

key stages to this learning process:

- data preparation: data uploading and feature engineering**

Data types:

- real-time streaming data or batch data,
structured (numbers and text normally saved in tables), or unstructured (images and videos).
- model training:** A model needs a tremendous amount of **iterative** training. This is when **training and evaluation** form a cycle to train a model, then evaluate the model some more.
- model serving.** move an ML model into production. the machine learning model is **deployed, monitored, and managed**.

ML workflow isn't linear, it's iterative:

during model training, you may need to **return** to dig into the raw data and **generate more useful features** to feed the model.

When **monitoring** the model during **model serving**, you might find **data drifting**, or the accuracy of your prediction might suddenly drop. You might need to **adjust the model parameters**.

Fortunately, these steps can be **automated with machine learning operations, or MLOps**.

Vertex AI provides many features to support the ML workflow:

- Feature Store:** provides a **centralized repository for organizing, storing, and serving** features to feed to training models,
- Vizier:** helps you **tune hyperparameters** in complex machine learning models,
- Explainable AI:** helps **interpret training performance and model behaviors**,
- Pipelines:** help you **automate and monitor the ML production**

Data preparation:

AutoML workflow

upload data, feature engineering

When you upload a dataset in the **Vertex AI user interface**, you'll need to provide a **meaningful name** for the data and then select the **data type** (image, tabular, or labeled)

A label can be **manually** added, or it can be added by using **Google's paid label service via the Vertex console**.

These **human labellers** will manually generate accurate labels for you.

Data can be uploaded from a local source, BigQuery, or Cloud Storage.

After your data is uploaded to AutoML, the next step is preparing the data for model training with feature engineering.

feature

a factor that contributes to the prediction.

an independent variable in statistics

a column in a table.

Preparing features can be both challenging and tedious. To help, Vertex AI has a function called **Feature Store**.

Feature Store: centralized repository to organize, store, and serve machine learning features.

Feature Store **aggregates all the different features from different sources** and updates them to make them available from a central repository

Vertex AI automates the feature aggregation to scale the process.

benefits of Vertex AI Feature Store:

features are **shareable** for training or serving tasks.

Features are **managed and served from a central repository**, which helps **maintain consistency** across your organization.

features are **reusable**. This helps save time and reduces duplicative efforts, especially for high-value features.

features are **scalable**. Features automatically scale to provide **low-latency serving**, so you can focus on **developing the logic to create the feature deployment**.

features are **easy to use**.

Model training:

model training, and model evaluation. This process might be iterative.

Artificial intelligence (AI): **anything related to computers mimicking human intelligence**.

Machine learning is a subset of AI that mainly refers to supervised and unsupervised learning.

deep learning, or deep neural networks: a subset of ML that **adds layers in between input data and output** results to make a machine learn at more depth

Supervised learning is **task-driven and identifies a goal**.

classification: predicts a categorical variable

regression model: predicts a continuous number,

Unsupervised learning, however, is **data-driven and identifies a pattern**:

clustering: groups together data points with similar characteristics and assigns them to "clusters,"

association: identifies underlying relationships

dimensionality reduction: reduces the number of dimensions, or features, in a dataset to **improve the efficiency** of a model.

with AutoML and pre-built APIs you **don't need to specify a machine learning model**.

you'll **define your objective**, such as text translation or image detection. Then on the **backend**, **Google will select the best model to meet your business**

With the other two options, BigQuery ML and custom training, you'll **need to specify which model** you want to train your data on and assign something

AutoML, you don't need to worry about adjusting these hyperparameter knobs because the tuning happens automatically in the **back end**.

This is largely done by a **neural architecture search**, which finds the best fit model by comparing the performance against thousands of other models

Model evaluation:

Vertex AI provides extensive evaluation metrics:

confusion matrix (recall and precision): specific performance measurement for machine learning classification problems.

false positive/negative : Type 1/2 Error

Precision and recall are often a trade-off:

If the goal is to **catch (as many potential)(all) spam emails as possible (FN->0)**, Gmail may want to prioritize **recall**.

In contrast, if the goal is to **only catch the messages that are definitely spam (FP->0)** without blocking other emails, Gmail may want to price

based on feature importance:

is displayed through a **bar chart** to illustrate **how each feature contributes to a prediction**.

feature importance is one example of Vertex AI's comprehensive machine learning functionality called **Explainable AI**

Explainable AI is a set of tools and frameworks to help **understand and interpret predictions** made by machine learning models.

Model deployment and monitoring:

model serving: **model deployment, model monitoring**

model management exists throughout this whole workflow to **manage the underlying machine learning infrastructure**

This lets data scientists focus on **what to do, rather than how to do it**.

MLOps combines **machine learning development** with **operations** and applies similar principles from **DevOps** to machine learning models, which i operations

MLOps aims (both data and code are constantly evolving in machine learning):

to solve **production challenges related to machine learning**.

building an **integrated machine learning system**

operating it in **production**

This means adopting a process to enable **continuous integration, continuous training, and continuous delivery**.

three options to deploy a machine learning model:

to deploy to an **endpoint**: is best when **immediate results with low latency** are needed, such as **making instant recommendations** based on a user's b online.

A model must be **deployed to an endpoint** before that model can be used to serve real-time predictions

to deploy using **batch prediction**:

This option is best when **no immediate response is required**, and **accumulated data** should be processed with a single request.

For example, **sending out new ads** every other week based on the user's recent purchasing behavior and what's currently popular on the market

to deploy using **offline prediction**:

This option is best when the model should be deployed in a **specific environment off the cloud**.

The backbone of MLOps on Vertex AI is a tool called **Vertex AI Pipelines**:

It **automates, monitors, and governs** machine learning systems by **orchestrating the workflow** in a **serverless** manner.

With **Vertex AI Workbench**, which is a **notebook tool**, you can **define your own pipeline**

Lab introduction: Predicting loan risk with AutoML:

AutoML requires **at least 1,000 data points** in a dataset.

Vertex AI: Predicting Loan Risk with AutoML:

[Vertex AI](#), the **unified AI platform** on Google Cloud to **train and deploy** a ML model:

Vertex AI offers two options on one platform to build a ML model:

a codeless solution with **AutoML**

a code-based solution with **Custom Training** using **Vertex Workbench**

There are three options to import data in Vertex AI:

- Upload a local file from your computer.
- Select files from Cloud Storage.
- Select data from BigQuery.

For **Budget**, which represents **the number of node hours for training**, enter **1**.

Training your AutoML model for 1 compute hour is **typically a good start for understanding whether there is a relationship between the features and**

The **confidence threshold** determines how a ML model counts the positive cases.

A **higher threshold increases the precision, but decreases recall**. A lower threshold decreases the precision, but increases recall.

You can improve the percentage by **adding more examples (more data)**, **engineering new features**, and **changing the training method**, etc.

These **feature importance** values could be used to help you improve your model and have more confidence in its predictions:

You might decide to **remove the least important features** next time you train a model or

to **combine two of the more significant features** into a **feature cross** to see if this improves model performance.

Feature crosses are mostly used with **linear models** and are rarely used with neural networks.

Now that you have a trained model, the next step is to **create an endpoint in Vertex**.

A model resource in Vertex can have **multiple endpoints** associated with it, and you can **split traffic between endpoints**.

To allow the pipeline to authenticate, and be authorized to **call the endpoint to get the predictions**, you will need to provide your **Bearer Token**.

To use the trained model (get predictions), you will need to **create some environment variables**.

The smproxy application is used to communicate with the backend.

Lab recap: Predicting loan risk with AutoML:

how high (TP, TN) or low (FP, FN) they need to be really depends on the **business goals** you're looking to achieve

to improve the performance of a model:

using a more accurate data source,

using a larger dataset,

choosing a different type of ML model,

tuning the hyperparameters.

Course Summary:

cloud.google.com/training/data-engineering-and-analytics

cloud.google.com/training/machinelearning-ai

cloud.google.com/certifications

How Google Does Machine Learning

Introduction to course and series:

Course series preview

Roles:

machine learning scientists,

machine learning engineers

data scientists,
data engineers and
data analysts

Tools:

Vertex AI platform,
BigQuery ML,
TensorFlow
Keras

machine-learning products and concepts:

Analytics Hub,
Dataplex,
Data Catalog,
predictions
model monitoring,
data quality improvement
exploratory data analysis

what it means to be AI-first :

Introduction:

build a data strategy around ML,
identify and solve ML problems,
infuse your applications with ML.

What kinds of problems can ML solve?

What is ML?

ML

Machine learning is a way to use standard algorithms to **derive repeated predictive insights from data** and **make repeated decisions**

So machine learning is about **making many predictive decisions** from data

It's about scaling up business intelligence and decision-making

backward-looking use of data: looking at historical data to create reports and dashboards.

AI vs ML: AI is a discipline, ML is a specific way of solving AI problems

The ML model is a **mathematical function**

ML has two stages: **training and inference (prediction)**.

each of the layers of the Neural networks are a simple mathematical function. The entire model therefore consists of a **function of a function of a function** and so on.

Training **deep neural networks**, neural networks with lots of layers, takes a lot of computing power

Google has more than **10,000** plus deep learning models

In practice, you have to build **many ML models to solve the problem**

Avoid the trap of thinking of building **monolithic "one model solves the whole problem"** solutions

Google Photos:

This is the Google product where you can **upload photos from your camera to the cloud**. You don't need to tag it. The **ML software tags images** for you so that **you can then find images**.

Google Translate: lets you point a phone camera at a street sign, and it translates the sign for you:

One model to find the sign,
another model to read the sign through OCR, optical character recognition,
a third model to detect the language,
a fourth model to translate the sign,
a fifth model to superimpose translated text,
perhaps even a sixth model to select the font to use and so on

Gmail's Smart Reply:

This is arguably **the most sophisticated** ML model in production today.

It's a **sequence-to-sequence** model.

What problems can it solve?

ML scales better than the Hand-coded rules, because it's all automated

RankBrain, a deep neural network for search ranking

the system could continually improve itself based on what users actually preferred.

Replacing **heuristic rules** by ML, that's what ML is about

What kinds of problems can you solve with ML?

Anything for which you're writing rules today.

Google is an **AI-first** company: Google thinks of ML as the way to **scale, to automate, to personalise**

Rule-based vs model-based application

- You don't think about **coding up rules**, you think about **training models based on data**.
- You don't think about **fixing bug reports by adding new rules**, you think in terms of **continuously training the model as you get new data**.
- And when you think of **applying rules to inputs**, you think in terms of **deploying models at scale to make predictions**.

Machine learning is about collecting the appropriate data, and then finding the right balance of good learning, trusting the examples

Activity intro: Framing a machine learning problem

Cloud ML use cases:

Manufacturing
Retail
healthcare and life sciences
travel and hospitality
financial services
Energy, feedstock and utilities.

Activity solutions: Framing a machine learning problem:

ML problem:

what is being predicted?
what data do we need?

software problem:

What is the API of the service?
what does it take?
who's going to use this service?
How are they doing it today?

data problem:

data problem:

- what kind of data do we need to collect?
- what data do we need to analyze?
- what is our reaction? How do we react to a prediction?

Infuse your apps with ML:

An easy way to add ML to your apps is to take advantage of pre-trained models.

Aucnet:

the new machine learning system can **detect the model number of the car** at high accuracy
 It can also show the estimated price range for each model
 and recognize what part of the car is being photographed
 With this system, the car dealers just drag and drop a bunch of unclassified photos and check if the model and parts are classified by the system correctly.
 Aucnet built a **custom** image model on Google Cloud platform using TensorFlow
 you don't have to do that. There are a variety of domains where Google exposes ML services trained with their own data (Pre-trained (vs custom) ML models):
 speech API: transcribe speech
 Vision API
 Translation API
 Natural Language API
 Jobs API
 Video Intelligence API

Ocado

is the world's largest **online-only grocery** based in the UK:
 They were able to get **sentiment** entities and **pausing** syntax.
 The computational technology helps Ocado **parse** through the body of e-mails, **tagging** and **routing** to help contact center reps determine the **priority and context**
 Ocado use **parsed results from the NLP API** to **route** customer e-mails.
 They don't want to send you an e-mail. They want to **talk to you interactively** to get their questions or concerns answered.
 we'll be spending more on **conversation interfaces** than even on **mobile apps**

Dialogflow

high level conversational agent tool

Giphy

uses the Vision API to **find the text in memes** using **optical character recognition**.
 The social media company used the Vision API to reject inappropriate uploads.

Uniqlo

designed a shopping chatbot using Dialogflow.

Build a data strategy around ML:

Google Maps

Where the roads are,
 the traffic on each road, bridge closures,
 Traffic and bridge closures are a little more difficult in that you have to work with a bunch of smaller government entities the algorithm itself,
 routing algorithms between A and B subject to a set of constraints.
 You're in a subway station called Roppongi, and Maps tells you that you're on floor number two
 Personalization of the map service is possible only with machine learning.
 Machine learning is about scaling beyond handwritten rules.
 asking for **user feedback to keep improving the model**

Given the choice between **more data and more complex models**, spend your energy collecting **more data**

That means collecting **not just more quantity, but also more variety**

An ML strategy is first and foremost a **data strategy**.

several reasons why you want to go through manual data analysis to machine learning:

if you're doing manual data analysis, you probably **have the data already**.
 Collecting data is often the **longest and hardest** part of an ML project and the one most likely to fail.
 Manual analysis helps you **fail fast and try new ideas in a more agile way**, so don't skip the analysis step.
 to build a good ML model, you have to **know your data**.

Since that's the first step, go through the process of doing manual data analysis, don't **jump straight** to ML.
 ML is a journey towards **automation and scale**.

training-serving skew:

This is where you had a certain system (**batch processing system**) for processing **historical** data so that you could **train** it
 Then you have a different system that needs to **use the ML model during prediction**.
 The system that serves these predictions is probably written in something that your **production engineering team** writes and maintains. Perhaps it's written in **Java** using **Web Frameworks**.
training-serving skew: The problem is that unless the model sees the exact same data in **serving** as was used to do **training**, the model predictions are going to be off

One way to reduce the chances of this is to take **the same code that was used to process historical data during training and reuse** it during **predictions**, but for that to happen, your **data pipelines have to process both batch and stream**.

This is a key insight behind **cloud dataflow**

a way to offer **data pipelines in Python, Java** or even visually with Cloud Dataprep.
 It's **open-sourced as Apache Beam**, where the B stands for **batch** and -eam stands for **stream**.
 A single system to do both batch and stream

in machine learning, it's helpful to use **the same system in both training and prediction**

During training, the key performance aspect you care about is **scaling to a lot of data (distributed training)**

During prediction, though, the key performance aspect is **speed of response**, high **QPS**.

This is a key insight behind **TensorFlow**.

the magic of ML comes with **quantity not complexity**.

If you're building many ML models and planning for many more that you may never build, you want to have an environment where you **fail fast**. The idea is that **if you're failing fast, you get the ability to iterate**.

Quiz:

ML training phase:

- Evaluating the models
- Data management
- Create the models

~~Connecting Neural Networks~~

to replace user input by machine learning?

~~Neural networks-~~

~~All options are correct-~~

~~labeled data-~~

Pre-trained models.

best practices for Data preparation

Avoid target leakage

Provide a time signal

Avoid training-serving skew

How Google Does ML:

machine learning,

we mean the process by which one computer writes a computer program (rule) to accomplish a task. which the best program is by only looking at a set of examples.

normal software engineering,

We have a human who analyzes the problem, writes a bunch of code, and then this code becomes a program that can translate inputs to outputs.

Fully end-to-end ML effort allocation:

defining the **KPI**,

what you should even be trying to accomplish,

collecting data,

building the infrastructure,

optimizing the ML algorithm itself (the most),

integrating with the rest of the pre-existing systems at your organization.

The secret sauce

Top 10 ML pitfalls:

ML requires just **as much software infrastructure**

you thought training your own ML algorithm would be faster than writing the software.

And the reason is that to make a great ML system, beyond just the algorithm, you're going to need lots of things around the algorithm. like a whole software stack to serve, to make sure that it's robust, and it's scalable, and has great uptime.

But then, if you try to use an algorithm, you put in additional complexities around **data collection, training**, and all of that just gets a little bit more complicated.

No data collected yet

If there's not someone in your organization who's **regularly reviewing that data** or generating reports or new insights, if that data isn't generating value already, likely, the effort to maintain it isn't being put in.

keep **humans in the loop**:

they're reviewing the data,

handling cases the ML didn't handle very well,

curating its training inputs.

You launched a product whose initial value prop was its ML algorithm instead of some other feature.

ML system, and it just happens to **optimize for the wrong thing**

if you forget to measure if your ML algorithm is actually **improving** things in the real world?

you confuse the ease of use and the value add of somebody else's **pre trained** ML algorithm with **building your own**

ML algorithms are going to be **retrained many times**

And in fact, all the algorithms we have to address these are **very highly tuned from decades of academic research**. And you should almost always take one off the shelf already made, or already kind of defined, instead of trying to do your own research, as that is very expensive.

ML and business processes:

business processes: any set of activities a company must do directly or indirectly to serve customers.

almost every one of them has a feedback loop.

General feedback loop:

Input-process-outputs-insight generation-tuning-process

The path to ML

Input-process(individual contributor,delegation,digitization)-outputs-insight generation(big data and analytics)-tuning(ML)-process

individual contributor

A task or business process that's in the individual contributor phase is performed by a single person.

The task is not parallelized or scaled at all and is usually very informal.

delegation

multiple people who are all performing the same task in parallel

there's some repeatability in the task

Digitization

we take the **core repeatable** part of the task or a business process, and we **automate** it with computers.

We want to give our users a higher quality of service

it involves so much upfront investment,

Big Data and analytics

we're going to use a lot of data to **build operational and user insights**.

ML:

Here we use all the data from the previous step.

We'll automatically start to improve these computer processes.

A closer look at the path to ML

individual contributor

Dangers of Skipping:

Inability to scale

incorrect assumptions that are hard to change later.

Dangers of Lingering

Imagine that you've got one person who's very skilled at their job but then leaves the company or retires.

All that organizational knowledges leaves with them. It's a problem when no one else can perform that process.

Also in this phase you can't scale up the process to meet a sudden increase in demand.

delegation

Dangers of Skipping:

you're never forced to formalize the business process and to define success.

Human responses have an inherent diversity

great ML systems will need humans in the loop

If your ML system is very important, it should be reviewed by humans

Dangers of Linger

you're paying a very high marginal cost to serve each user

The more voices you have in your organization, automation is less possible.

This creates a kind of **organizational lock-in** because you have too many **stakeholders**

Digitization

Dangers of Skipping:

you'll need all the infrastructure of this step to be able to serve your ML at scale

you might start to untangle an IT project, which we may call software, with an ML project. If either one of them fails, the whole project fails.

Dangers of Linger

the other members of your industry are collecting data and tuning their offers and operations from these new insights

Big Data and analytics

Dangers of Skipping:

you won't be able to train your ML algorithm because your data isn't clean and organized

you can't build a measure of success

Dangers of Linger

limiting the **complexity** of problems you can solve and the **speed** at which you can solve them

End of phases deep dive

Almost every single one has a team of people reviewing the algorithms, reviewing their responses and doing random sub-samples and it generates a lot of value for the organization, for customers and for end users.

facets that differentiate deep learning networks in multilayer networks?

More complex ways of connecting layers

Cambrian explosion of computing power to train

Automatic feature extraction

ML development with Vertex AI

Introduction

To build an ML for production

identifying a goal,

acquiring, exploring, and preparing data,

building,

training,

evaluating the model.

Deployment (**web client** that can **request** predictions from the model)

monitored

maintained.

the proof of concept, or experimentation phase: the process of determining whether the model is **ready for production**

Moving from experimentation to production

ML development during the experimentation phase:

framing the problem

you identify your use case,

questions typically asked are what you're trying to do? What are the minimum requirements of your business application?

preparing the data,

you might use a subset of a larger data set.

You would also perform **EDA** or exploratory data analysis and seek to improve data quality

You'd also consider combining features to create a new feature (**Feature engineering**)

experimenting,

you experiment with different models to compare performance metrics.

evaluating the model

recall, precision, an F1 score, or cross-entropy

ML practitioners train models using

different architectures,

CNNs, or convolutional neural networks are used for image classification, object detection, and recommender systems.

RNNs or recurrent neural networks are used for sequence modeling, next word prediction, translating sounds to words and human language translation.

Sorting and clustering architectures are used for anomaly detection, and pattern recognition.

GANS, or generative adversarial networks are used for anomaly detection, pattern recognition, cybersecurity, self-driving cars, and reinforced learning.

different input datasets,

numerical data sets,

bivariate data sets,

multivariate data sets,

categorical data sets,

correlation data sets

different hyperparameters

learning rate,

number of layers,

num_estimators,

max_depth

different hardware

CPUs,

GPUs,

TPUs

Moving from experimentation to production requires:

packaging

package As you package your code for production, you need to **build and install a Python package** out of your predictive model in Python.

deploying,

A trained module can be deployed in various ways, such as on a **user's mobile device**, or as a **web service in a container running on a cluster**.

Deploying the model also requires you to **set up endpoints** which allow your app to serve predictions.

a machine learning model can have a **web app front end**. a **request** is sent by a **web client** using a **REST API**, a prediction made by the model is returned.

monitoring your model

model stale: the underlying data distribution may have shifted over time

the model may have been **misconfigured** in its production deployment

Then, a **model retraining deployment pipeline** can be triggered

Monitoring measures key model performance metrics, and includes

- model drift,

- model performance,

- model outliers

- data quality