Data science and AI applications in eCommerce

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Agenda

- Introduction
- Case study 1 Decision Engine
- Case study 2 Vertex Al
- Case study 3 Cloud Functions & Bigquery
- Q&A



Introduction



An overview of Logickube

We partner with leading cloud providers to provide AI and Data services to leading retailers in APAC

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Strategic advisory on Al

Build out a strategic roadmap and Proof-Of-Concepts models in collaboration with our technology and data experts to accelerate your Al journey.

Cloud data engineering

Maximise the advantages of new technologies in the cloud by modernizing your data and ML workloads in a scalable and secure manner.

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Al engineering

Build best in class data and model pipelines to produce your own state of the art Al capabilities across retail, digital media, financial services and health.



Personalisation & Attribution

Tailor unique interactions for each customer, across marketing channels and store experiences. Quantify personalisation benefits with robust experiment design and attribution.









Maths/Statistics is the cornerstone

Designing the right model to solve the right problem

- A systematic process to identify and define problems
- Always design the most suitable solution for each specific problem

Interpreting models and creating actionable insights

- Make black boxes transparent
- Translate maths/stats into business language

Experimental design / getting the right data

- Validate maths/stats tools in a real-world context
- Disentangle factors that jointly contribute to business success

Innovation and R&D

• Develop novel, mathematically sound methods adapting to ever-changing business needs



Cloud computing is our go-to skillset

Leveraging cloud computing could significantly boost the performance of data and AI products

- Data **availability** and **reliability** Data are replicated and stored in different locations, easy to backup and restore data in case of any failure
- **Big data capability** and high **efficiency** e.g. we use Databricks to optimise performance, enabling real-time data processing, message producing and delivery
- Cost effective
 - Reduced cost of maintaining hardware and software
 - 'Pay-as-you-go': cost is only generated for what/when is used
 - Various tiers of computing power and storage classes

Cloud based solutions provide a good level of data security

- Advanced security features ensure data is securely stored and handled
- Data encryption in transit and at rest
- Certain protocols may be enforced to strengthen security

Our team has relevant **experience** and **qualifications**

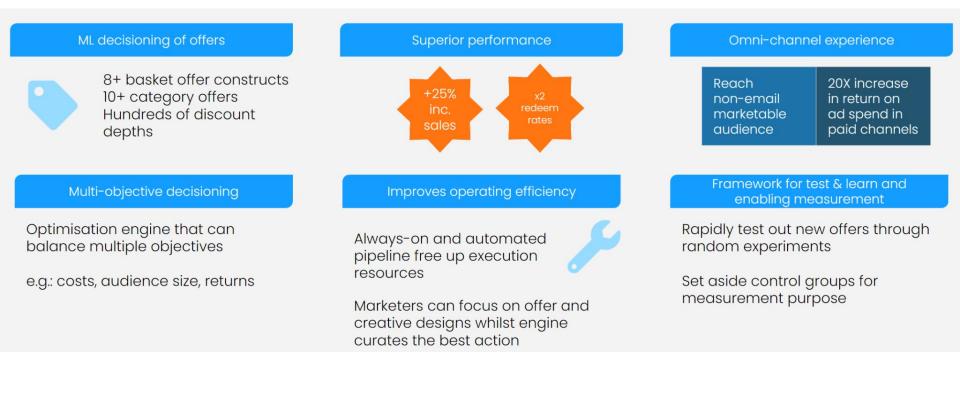
- Certified data scientists, data engineers, machine learning engineers and solution architects across mainstream cloud platforms
- Highly experienced in building scalable cloud solutions to create end-to-end data and AI solutions



Case study 1 Decision Engine

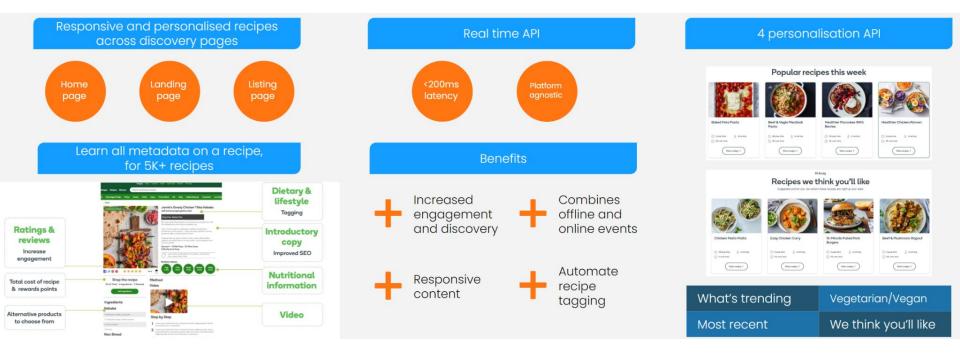


Decision Engine offering





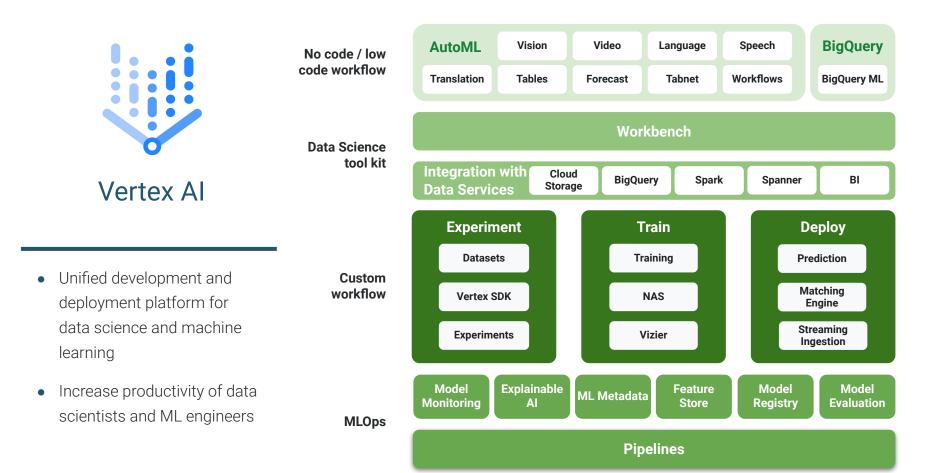
Decision Engine key features





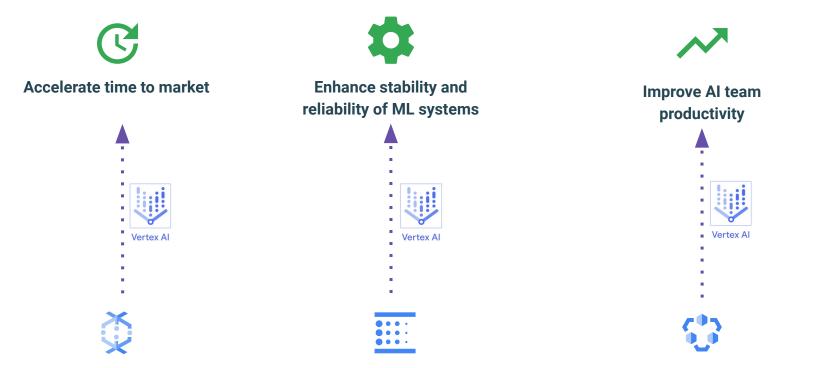
Case study 2 Vertex Al







What Data Science & Machine Learning Engineering teams want



Unified data and AI platform for all users to accelerate time to value

End-to-end MLOps to efficiently and responsibly manage and govern AI

Open and scalable AI infrastructure to flexibly and successfully deploy AI



Vertex AI is a platform for all users throughout the ML lifecycle



Data analyst Query and analyse

Endless EDW BigQuery

Self-managed data pipelines Cloud Data Fusion, Dataflow

Data models, catalog Looker, Data Catalog

Machine learning in SQL BigQuery ML



Data engineer Get clean, useful data

Self-driving infra BigQuery, Dataflow, Cloud Composer

Broad choice of tools/language Dataproc, Dataflow

Data quality /lineage Vertex Al, BigQuery, Dataflow

Real-time capabilities BigQuery, Dataflow Data scientist Models that work

Portable notebooks Managed Notebooks

Model eval and selection Vertex Explainable AI, Vertex AI Experiments

Point-and-click dev AutoML

Collaboration Vertex AI Feature Store, Vertex AI Pipelines



ML engineer Models in production

Scalable model hosting Vertex AI Prediction

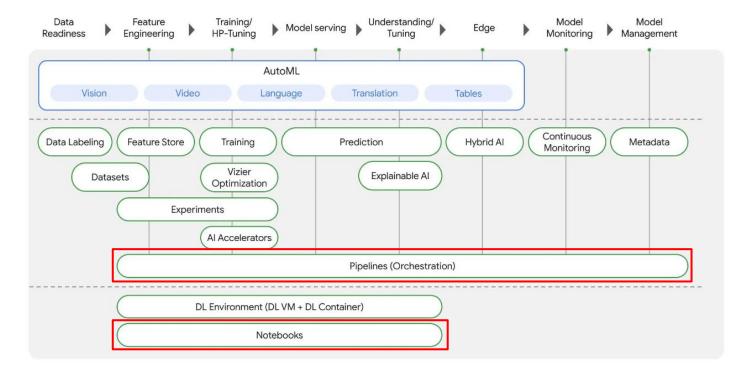
ML CI/CD and orchestration Vertex AI Pipelines

Provenance and lineage Vertex ML Metadata

Improvements and retraining Cloud Monitoring

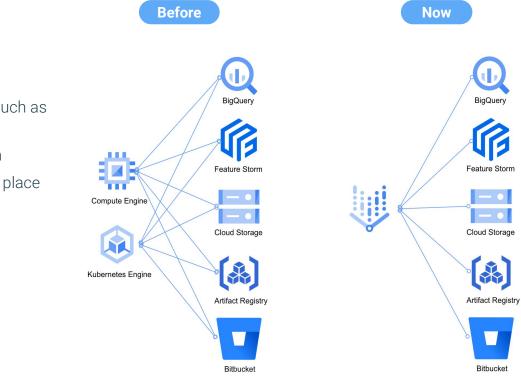


Vertex AI for large enterprises





Vertex AI for large enterprises



- Vertex AI enables seamless connections with data sources such as BigQuery and Cloud Storage
- Less infrastructure configuration
- End-to-end ML workflows in one place



Vertex Al Workbench: One-stop surface for data science

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Fully managed compute with admin control

A Jupyter-based fully managed, scalable, enterprise-ready compute infrastructure with easily enforceable policies and user management



Fast workflow for data tasks

Seamless visual and code-based integrations with data & analytics services

At-your-fingertips integration

Load and share notebooks alongside your AI and data tasks. Run tasks without extra code

| Google Cloud Platf | orm 🐌 mchrestkha-sandbox 👻 🔍 🔍 | Search Products, | resources, docs | (/) | | | ~ |
|----------------------------|---|------------------------------|--------------------------|-----------------------------------|--------------------------------|--------------------------------------|-----------------|
| Vertex Al | Workbench ENEW NOTEBOO | C REFRESH | ▶ START | ∎ STOP Č |) RESET 👕 DEI | .ETE | |
| Dashboard | MANAGED NOTEBOOKS PREVIEW US | ER-MANAGED NOTEB | OOKS EXE | CUTIONS PREVIE | W SCHEDUL | ES PREVIEW | |
| Datasets | Managed notebooks provide JupyterLab servi | | ting resources | | | | |
| Features | integrated with Google Cloud services. Learn | nore | | | | | |
| Labeling tasks | Region us-central1 (lowa) 🗸 🔮 | | | | | | |
| Workbench | Filter Enter property name or value | | | | | | |
| Pipelines | ■ Notebook name ↑ | | | | Location | Access mode | |
| Training | managed-notebook-1 | 543391246 | OPEN JUPY | TERLAB | us-central1-f | Single user only | |
| Experiments | managed-notebook-1 | 543393492 | OPEN JUPY | TERLAB | us-central1-c | Single user only | |
| Models | managed-notebook-1 | 547318683 | OPEN JUPY | | us-central1-c | Single user only | |
| Endpoints | mchrestkha-sandbox nvidia-ngc | | OPEN JUPY OPEN JUPY | | us-central1-a us-central1-f | Single user only Single user only | |
| Edge deployments | tf-mnist-ngc | | OPEN JUPY | TERLAB | us-central1-f | Single user only | |
| Batch predictions Metadata | mchrestkha-sandbox Petverv ↓ File Edit View Run Kernel Git Tabs Sett + 12 ± C ↔ Filter files by name Q | | | | | 4 vCPUs 1 34.7% | 5 GB RA 6.1% |
| @ | m / | Notebook | ¢ | | | Modify hardware | |
| ≡ 0 ♦ | Name A Last Modified In src 7 minutes ago In tutorials 7 minutes ago | Python (Local) | Spark PySpark (Local) | PySpark on cluster-5977-m | Python 3 on cluster-5977-m | C Pytorch (Local) R (Loc | - |
| ≔ | | ** | T | XGBoost | | | |
| 6 | | spylon-kernel on cluster- | TensorFlow 2 (Local) | XGBoost (Local) | | | |
| * | | >_ Console | | | | | |
| | | Python (Local) | Spark PySpark (Local) | P PySpark on cluster-5977-m | Python 3 on cluster-5977-m | C Pytorch (Local) R (Loc | 2 al) |



Benefits

Easy data exploration and analysis with Easy access to data in BigQuery and Cloud Storage within a Jupyter notebook

| | <pre>%bigquery regions_by_country SELECT</pre> | | | | | | | | | |
|------|--|--|--|--|--|--|--|--|--|--|
| | country_code, | | | | | | | | | |
| | country_name, | | | | | | | | | |
| | COUNT(DISTINCT r | egion_code) AS r | num_regions | | | | | | | |
| | FROM | | | | | | | | | |
| | `bigquery-public WHERE | -data.google_tre | ends.international_top_terms` | | | | | | | |
| | refresh_date = D GROUP BY | ATE_SUB(CURRENT_ | _DATE, INTERVAL 1 DAY) | | | | | | | |
| | country_code, co | untrv name | | | | | | | | |
| | ORDER BY | /_ | | | | | | | | |
| | num_regions DESC | , | | | | | | | | |
| | Query complete aft | er 0.19s: 100% | 4/4 [00:00<00:00, | | | | | | | |
| 51: | Downloading: 100% | 41/4 | 4/4 [00:00<00:00, 41 [00:02<00:00, 16.35rows/s] | | | | | | | |
| 5]: | Downloading: 100% | info() | 41 [00:02<00:00, 16.35rows/s] | | | | | | | |
| [5]: | Downloading: 100% regions_by_country <class 'pandas.cor<="" td=""><td>• info() e.frame.DataFram</td><td>41 [00:02<00:00, 16.35rows/s]</td></class> | • info() e.frame.DataFram | 41 [00:02<00:00, 16.35rows/s] | | | | | | | |
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| [5]: | Downloading: 100% regions_by_country <class 'pandas.cor<br="">RangeIndex: 41 ent Data columns (tota # Column</class> | e.frame.DataFram ries, 0 to 40 l 3 columns): Non-Null Count | 41 [00:02<00:00, 16.35rows/s] ne'> | | | | | | | |
| [5]: | Downloading: 100% regions_by_country <class 'pandas.cor<br="">RangeIndex: 41 ent Data columns (tota # Column </class> | 41/4 .info() e.frame.DataFram ries, 0 to 40 l 3 columns): Non-Null Count 41 non-null | 11 [00:02<00:00, 16.35rows/s] ne'> Dtype object | | | | | | | |
| [5]: | Downloading: 100% regions_by_country <class 'pandas.cor<br="">RangeIndex: 41 ent Data columns (tota # Column 0 country_code 1 country_name</class> | 41/4 .info() e.frame.DataFram ries, 0 to 40 l 3 columns): Non-Null Count 41 non-null | 11 [00:02<00:00, 16.35rows/s] ne'> Dtype | | | | | | | |
| [5]: | Downloading: 100% regions_by_country <class 'pandas.cor<br="">RangeIndex: 41 ent Data columns (tota # Column 0 country_code 1 country_name</class> | 4174 .info() e.frame.DataFram ries, 0 to 40 l 3 columns): Non-Null Count | 11 [00:02<00:00, 16.35rows/s] ne'> Dtype | | | | | | | |

Fast prototyping and model development by creating a new notebook under 1 minute and connecting to other GC services within it





User-Managed Notebook

User-managed notebooks are high customisable VM instances and suitable for data exploration, analysis and model development

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A preinstalled suite of ML/DL packages

| + NEW NOTEBOOK | CREFRESH | ► START | STOP | U RESET |
|---------------------------|----------------------|-----------------|------------------|---------|
| Customize | | | | |
| Python 3 | | | | |
| Includes scikit-learn, pa | andas and more | | | |
| Python 3 (CUDA Too | olkit 11.0) | | | |
| Optimized for NVIDIA (| SPUs | | | |
| TensorFlow Enterpr | se | | | |
| Includes Keras, scikit-le | earn, pandas, NLTK | and more | | ×. |
| PyTorch 1.13 | | | | |
| Includes scikit-learn, pa | andas, NLTK and m | ore | | |
| R 4.2 | | | | |
| Includes basic R packa | ges, scikit-learn, p | andas, NLTK and | d more | |
| Kaggle Python [BET | A] | | | |
| Python image for Kagg | le Notebooks, sup | porting hundred | s of machine | • |
| learning libraries popul | | | | |
| JAX 0.3.14 [EXPERI | | | | |
| Data science framewo | | ning research a | nd optimizing ru | n- |
| time for scientific com | putations | | | |
| Smart Analytics Fra | meworks | | | |
| BigQuery, Apache Bear | | nacho Hivo and | more | • |

Similar setup process to GCE

| Details | Environment |
|------------------|--|
| Environment | All environments use JupyterLab 3 by default and have the latest NVIDIA GPU and Intel libraries and drivers installed. You can specify a previous version instead. Learn more Q |
| Machine type | Operating system * |
| Disks | Debian 10 |
| Networking | Python 3 (with Intel® MKL) |
| IAM and security | Selected CUDA libraries provided if GPUs are selected. Includes key packages for handling data, such as scikit-learn, pandas and NLTK. |
| System health | Version |
| | Use the latest version |
| | O Use a previous version To learn more about specific Deep Learning VM versions, see the Deep Learning VM relear notes. [2] |
| | Post-startup script BROWSE |
| | Cloud Storage path to script that automatically runs after the instance boots up |
| | Metadata |
| | Some metadata keys including enable-oslogin, framework, notebooks-api, nvidia-driver gcs-path, proxy-url, restriction, shutdown-script, title, version are reserved for system us |
| | only. If you use these variable names below, they will be overwritten by system values. |
| | |



Managed Notebook vs User-Managed Notebook

| Feature | Managed Notebook | User-Managed Notebook |
|----------------------------|--------------------------|-------------------------------|
| Flexibility | Low | High |
| Custom environment | Yes | Yes |
| Switch machine type | Within JupyterLab | Shutdown, switch, and restart |
| GCS navigation | Within JupyterLab | In GCS |
| BigQuery navigation | Within JupyterLab | In BigQuery |
| Scheduled runs | Supported | Not supported |
| Management fees | \$0.05 per vCPU per hour | \$0.005 per vCPU per hour |
| Idle shutdown | Supported | Not supported |

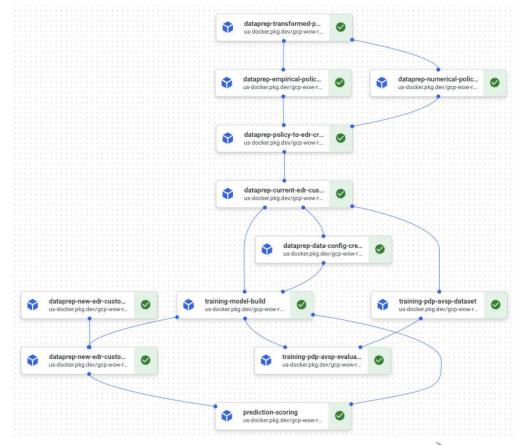


Productionise Models in Vertex AI

Vertex Al **Pipelines** orchestrate ML workflows serverlessly, and automate and monitor repeatable workflows such as model training and production.

Benefits:

- Serverless service
- Lower costs
- Workflow automation
- Composable and reusable pipelines
- Python function-based components



loaickube

When to use Pipelines



Train/productionise models with well-defined and reusable workflows

When ML workflows are finalised and will be reused for multiple times, consider packaging the dependencies into a Docker image and migrate the workflows from notebook to Pipelines to save time and improve reliability.



Automate model training/production

Manual weekly/monthly model scoring or refitting could be tedious, and schedule pipeline execution or trigger pipeline runs with Pub/Sub could be a game changer.



Scalable model production

Built on top of Kubernetes, Vertex AI Pipelines are serverless and scalable. Users are able to specify different level of resources for different steps and design parallel processing to boost speed.



Automate Model Training/Production

Model training/production can be automated by scheduling or triggering pipeline runs.

To schedule pipeline runs, Cloud Scheduler and Cloud Functions are also needed other than Vertex AI

- Configure Cloud Scheduler to send a JSON string to Cloud Functions on your pre-defined schedule
- Cloud Functions that you build will parse the JSON string and submit pipeline runs using ingested parameters
- Pipeline runs





Case study 3 Cloud Function & Bigquery



A Multi-agent Orchestration Problem

- Multiple teams in the company collaborate for a common business (orchestration);
- They have different preferences in data transfer methods (Gmail, RDMS, Google Drive);
- They use different technical tools (GCP, Azure, AWS);
- They own different domain knowledge (BI, DA, DS);



connecting different platforms

running long-term services



Solution to the Orchestration Problem

Serverless Architectures

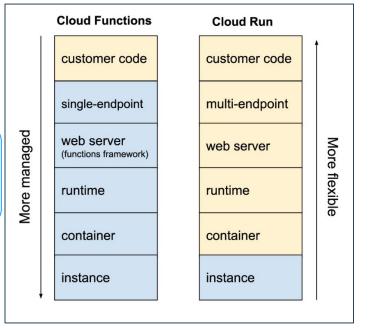
- Faster solutions to market at lower cost
- Decreased management overhead than traditional approaches

Cloud Function v.s. Cloud Run

- Cloud Function
 - Transforming data and loading it into BigQuery
 - Creating data summary once a BigQuery table gets updated
 - Use ML APIs to analyze data added to a database or storage bucket
- Cloud Run
 - Any web-based workload
 - REST APIs for mobile apps or games
 - Internal custom backoffice apps

Google Cloud Function

- Function-as-a-service (FaaS) in Google Cloud;
- Serverless architectures with pay-as-you-go convenience;
- Connection or extension to services with complex applications;
- Remedy to reconcile orchestration problems;







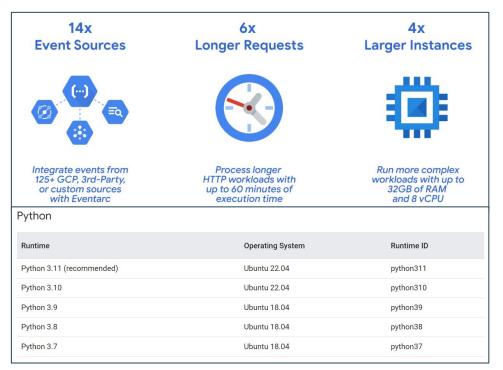
Main Features of Google Cloud Function (GEN 2)

Increased compute with granular controls

- Instance concurrency (up to 1000 requests/instance)
- Fast rollbacks (version control)
- 6x longer request processing (max. 60 minutes)
- 4x larger instances (max 16GB RAM + 4 vCPUs)
- Pre-warmed instances (fast configuration)
- Support multiple programming languages
- Extensibility and portability (to Cloud run)

Empowering Business Intelligence

- Inclusive to contributors from different backgrounds;
- Enable non-SQL functionalities;
- Combine complex operations in one go;
- Seamless data/messages digestion + broadcast;



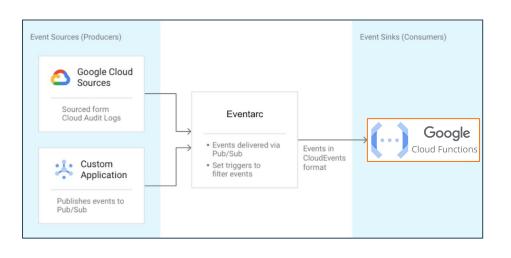
Node.js, Go, Java, Ruby, PHP, .NET Core

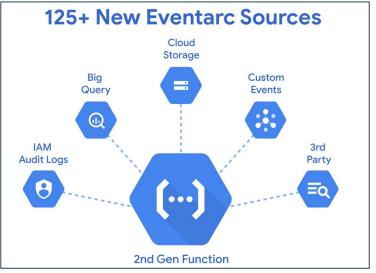


Main Features of Google Cloud Function (GEN 2)

Lots more event sources with the Eventarc

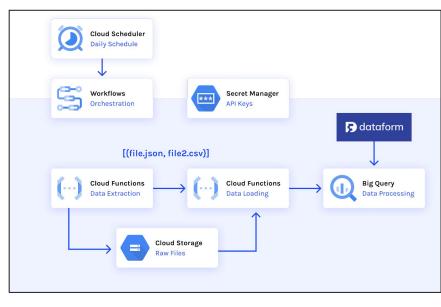
- 125+ Event sources (BigQuery, GCS, API Keys)
- Standards-based Event schema for consistent developer experience
- Customer-Managed Encryption Keys (CMEK) support



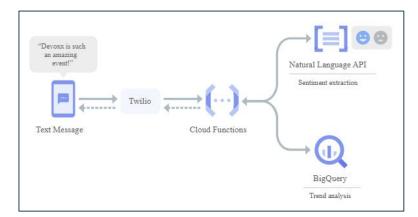




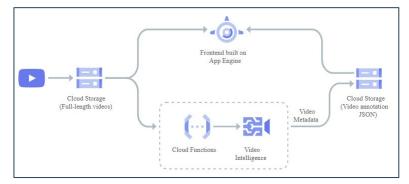
Orchestration Connected by Cloud Functions



Simple ETL Workflow



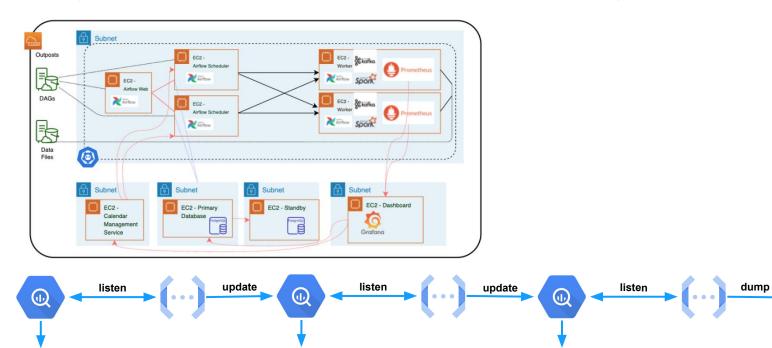
Real-time Text Messages Recognition and Logging



Transfer Video Objects to GCS



Comparison to Conventional Orchestration Pipeline



BQ Table 3

BQ Table 2

BQ Table 1



BigQuery ML Overview



```
#standardSQL
CREATE MODEL `bqml_tutorial.sample_model`
OPTIONS(model_type='logistic_reg') AS
SELECT
IF(totals.transactions IS NULL, 0, 1) AS label,
IFNULL(device.operatingSystem, "") AS os,
device.isMobile AS is_mobile,
IFNULL(geoNetwork.country, "") AS country,
IFNULL(totals.pageviews, 0) AS pageviews
FROM
`bigquery-public-data.google_analytics_sample.ga_sessions_*`
WHERE
_TABLE_SUFFIX BETWEEN '20160801' AND '20170630'
```

BigQuery ML is a part of enterprise BigQuery that allows you to create and execute ML models using Google SQL queries.



Why Use BQML?



Easy adaptation

- Develop ML models using the language you are comfortable with
- No need to learn Python or Java and ML frameworks such as TensorFlow or PyTorch



Increased development speed

- No need to move data in/out of BQ throughout the entire ML lifecycle.
- Bring ML to data, not the other way around.
- No need to wait for limited resources of data science team



No more time wasted on setup

- BigQuery is serverless so no need to provision VMs for model training
- Ready to develop no extra setup required such as installing frameworks and other dependencies



BQML - Supported Models

Internally trained

| Regression | • | Linear regression |
|----------------|---|----------------------|
| Classification | | Logistic regression |
| Others | • | K-means clustering |
| | • | Matrix factorisation |
| | • | PCA |
| | • | Time series |
| | | forecasting |
| | | |

Externally trained (Vertex AI)

| Regression | • DNN |
|----------------|------------------------|
| | • Wide & Deep Networks |
| | Boosted Tree |
| | Random forest |
| | AutoML Tables |
| Classification | • DNN |
| | Wide & Deep Networks |
| | Boosted Tree |
| | Random forest |
| | AutoML Tables |
| Others | Autoencoder |



BQML in Google ML Landscape

Out of box



CREATE OR REPLACE MODEL 'bqml.penguins_model' OPTIONS (model_type='linear_reg', input_label_cols=['body_mass_g']) AS SELECT * FROM 'public-data.ml_datasets.penguins' WHERE body_mass_g IS NOT NULL

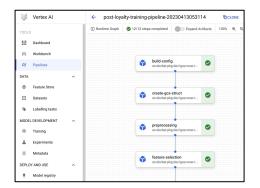
Pre-trained APIs & solutions

Cloud Vision API Speech-to-Text API

...

Custom AI with BQML and AutoML

No-code/low-code approach



DIY

End-to-end AI with core tools

Vertex AI and TensorFlow give data scientists strong control to build and deploy models



Import and Export Models in BQML

You can import the following models trained outside BQML and use them to perform prediction within BQ:

- Open Neural Network
 Exchange (ONNX) format
- TensorFlow Saved Model format
- TensorFlow Lite format
- XGBoost Booster format

BQML

You can export most models trained in BQML in the following formats and use them in other environment:

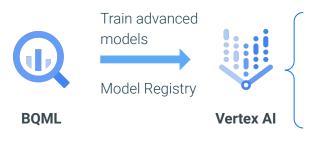
- TensorFlow Saved Model format
- XGBoost Booster format



Integrate BQML in Vertex AI

Advanced BQML models are usually trained in Vertex AI, which is Google's unified ML platform.

Integrating BQML in Vertex AI gives you online model serving capabilities and allows you to manage BQML models just like any other ML models via Model Registry.



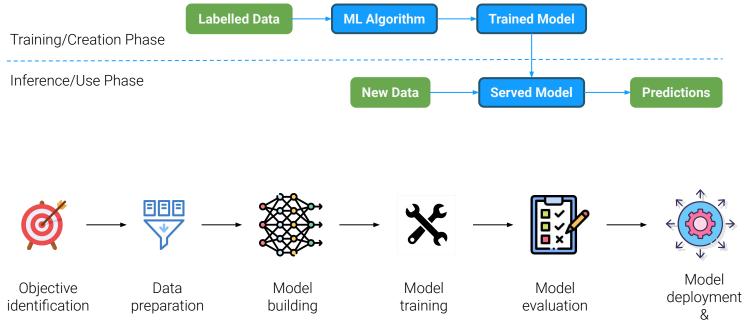
- All models managed in one place
- Model versioning and

comparison

- Model monitoring
- Online prediction
- Batch prediction



Typical machine learning workflows



maintenance



Create a BQML model using CREATE MODEL

| Row | species | island | culmen_length | culmen_depth | flipper_length | body_mass_g | sex | | bqml_demo 💽 RUN 🗳 SAVE 👻 🔩 SHA |
|-----|--------------------------------|--------|---------------|--------------|----------------|-------------|--------|----|---|
| 1 | Adelie Penguin (Pygoscelis ade | Dream | 36.6 | 18.4 | 184.0 | 3475.0 | FEMALE | 1 | 1 #standardSOL |
| 2 | Adelie Penguin (Pygoscelis ade | Dream | 39.8 | 19.1 | 184.0 | 4650.0 | MALE | 2 | <pre>2 CREATE OR REPLACE MODEL `bgml_demo.penguins_model`</pre> |
| 3 | Adelie Penguin (Pygoscelis ade | Dream | 40.9 | 18.9 | 184.0 | 3900.0 | MALE | 3 | 3 OPTIONS |
| 4 | Chinstrap penguin (Pygoscelis | Dream | 46.5 | 17.9 | 192.0 | 3500.0 | FEMALE | | <pre>4 (model_type='linear_reg',</pre> |
| 5 | Adelie Penguin (Pygoscelis ade | Dream | 37.3 | 16.8 | 192.0 | 3000.0 | FEMALE | | 5 input_label_cols=['body_mass_g']) AS |
| 6 | Adelie Penguin (Pygoscelis ade | Dream | 43.2 | 18.5 | 192.0 | 4100.0 | MALE | 7 | 6 SELECT 7 * |
| 7 | Chinstrap penguin (Pygoscelis | Dream | 46.9 | 16.6 | 192.0 | 2700.0 | FEMALE | 8 | 8 FROM |
| 8 | Chinstrap penguin (Pygoscelis | Dream | 50.5 | 18.4 | 200.0 | 3400.0 | FEMALE | 9 | <pre>9 `bigquery-public-data.ml_datasets.penguins`</pre> |
| 9 | Chinstrap penguin (Pygoscelis | Dream | 49.5 | 19.0 | 200.0 | 3800.0 | MALE | 10 | |
| 10 | Adelie Penguin (Pygoscelis ade | Dream | 40.2 | 20.1 | 200.0 | 3975.0 | MALE | 11 | 1 body_mass_g IS NOT NULL |

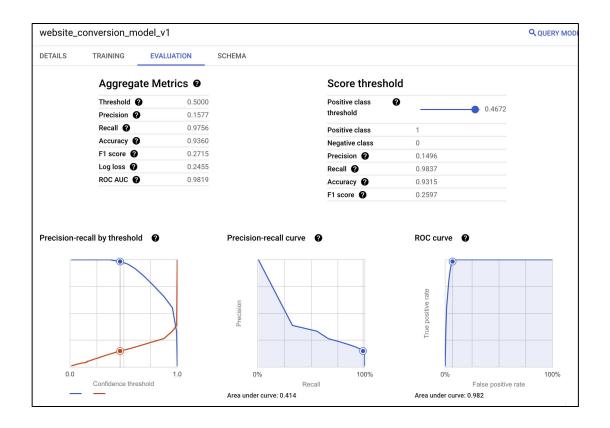
Label



Evaluate a BQML model

Evaluation is often automatically done during model creation in BQML, to early stop the model training process to avoid **overfitting**.

The validation set is used in this process, so it is also known as **validation**.





Use a BQML model using ML.PREDICT

Use your trained model to make predictions on new data, e.g., in model production.

| ۹Ĵ | model_predict_website_conversion 🛛 🖸 SAVE 🗸 |
|----|--|
| 1 | SELECT |
| 2 | * |
| 3 | FROM |
| 4 | ML.PREDICT(MODEL `bi-workshop-2023-92764.bqml_demo.website_conver |
| 5 | (|
| 6 | SELECT |
| 7 | IFNULL(device.operatingSystem, "") AS os, |
| 8 | <pre>device.isMobile AS is_mobile,</pre> |
| 9 | <pre>IFNULL(geoNetwork.country, "") AS country,</pre> |
| 10 | IFNULL(totals.pageviews, 0) AS pageviews, |
| 11 | IFNULL(totals.timeOnSite, 0) AS time_on_site |
| 12 | FROM |
| 13 | `bigquery-public-data.google_analytics_sample.ga_sessions_*` |
| 14 | WHERE |
| 15 | _TABLE_SUFFIX BETWEEN '20170701' |
| 16 | AND '20170801')) |

| JOB IN | IFORMATION | RESULTS | JSON EXECUT | TION DETAILS | EXECUTION | GRAPH PREV | /IEW | |
|--------|-----------------|------------------|----------------|---------------|-----------|------------|-----------|--------------|
| Row | predicted_label | predictlabel 👻 🏿 | predict prob 💌 | os 🔻 | is_mobile | country 👻 | pageviews | time_on_site |
| 1 | 0 | 1 | 0.020687784796 | BlackBerry | true | Indonesia | 2 | 20 |
| | | 0 | 0.979312215203 | | | | | |
| 2 | 0 | 1 | 0.017014568063 | BlackBerry | true | Indonesia | 1 | 0 |
| | | 0 | 0.982985431936 | | | | | |
| 3 | 0 | 1 | 0.015617142330 | Samsung | true | India | 1 | 0 |
| | | 0 | 0.984382857669 | | | | | |
| 4 | 0 | 1 | 0.014443974952 | Windows Phone | true | India | 1 | 0 |
| | | 0 | 0.985556025047 | | | | | |
| 5 | 0 | 1 | 0.014605231870 | Windows Phone | true | Romania | 1 | 0 |
| | l | 0 | 0.985394768129 | | | | | |







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