The Team & Agenda





Camus Ma AI/ML Lead (Google Cloud)



Ayan Kar EMEA Head of Data & AI (Capgemini)

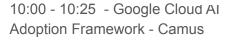


Luc Schamhart Account Manager Nationale-Nederlanden





Joost Carpaii Insight/Data Consultant (Capgemini)



10:25 - 10:50 - Applying Al governance & ML Opps.& Glassbox Demo - Ayan & Bikas

10:50 - 11:00 - Stretch legs

11:00 - 11:45 - Google Cloud Vertex Framework -Turan (incl. demo)

11:45 - 11:55 - Experience @ NN (Life & Pensions) Joost

11:55 - 12:20 - Cool Demo's Marijn

12:20 - 13:00 - Lunch



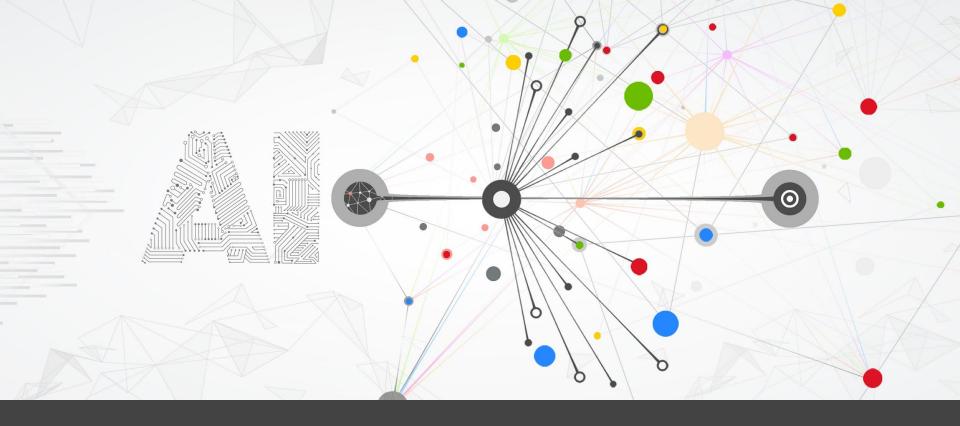
Turan Bulmus AI/ML Practice Lead Benelux



Marijn Markus AI/ML Consultant (Capgemini)

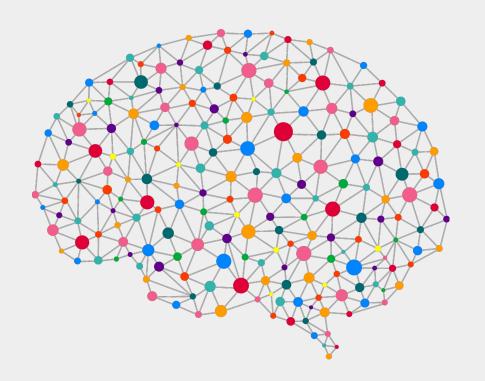








Google Cloud's Al Adoption Framework



Gain a competitive advantage through Al

Enterprises that invest in building industry-specific Al solutions are proven to be better positioned as future global economic leaders

Companies that fully absorb Al could double their cash flow

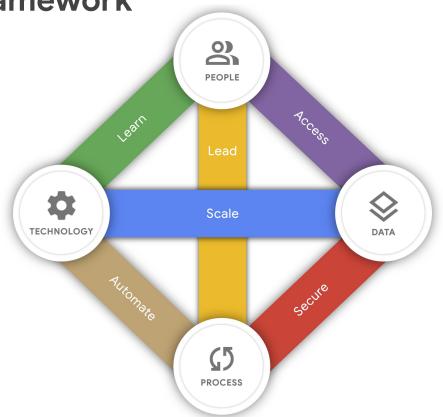
2X more data-driven decisions 5X faster decisions than others

3X faster execution

Sources: McKinsey 2018 and MIT Tech Review 2017

The Cloud Al Adoption Framework

- A guiding framework for leaders who want to leverage the power of Al to transform their business
- A tool to assess where you are in your journey and define where you want to be



Al Maturity Themes



How are the teams structured?

What is the level of executive sponsorship?

How is budget allocated for AI/ML projects?



How are cloud-based services provisioned?

How is capacity for workloads allocated?

Does an organization use accelerators?



What the data and ML skill sets are required in the organisation?

How does an organization develop ML talent?



What controls are in place?

How does an organisation establish trust in it's AI capability?

Can you explain the decisions made by your Al systems?



How are datasets created, curated, and annotated?

Are they discoverable and reusable?

How are data and ML assets managed?



How models are continuously trained and deployed for serving?

How are model updates managed?

What ML quality control are in place?

Al Maturity Phases

Strategic

Transformational

- Focus on narrow, simple use cases
- Good foundational skill set for core data wrangling and descriptive analytics
- Benefit from improved actionable insights from data

- Several ML systems deployed and maintained in production
- Degree of centralised coordination through an Advanced Analytics team
- Customised models can be a source of competitive advantage

- Continuous ML training and serving (MLOps)
- Culture where experimentation and learning is continuous
- Cutting-edge research, a point of differentiation to attract the best talent

The Cloud Al Maturity Scale

Lead

PEOPLE Lead PROCESS

The theme concerns the extent to which your data scientists are supported by a mandate from leadership to apply ML to business use cases, and the degree to which the data scientists are cross-functional, collaborative, and self-motivated.

Tactical

- Al adoption driven by individual contributors
- "Heroic" project manager with team budget
- Al/ML link to business goals not always clear

Strategic

- Creating a centralized cross-functional advanced analytics team to establish common ML patterns and practices
- Senior executive sponsorship and dedicated budget by C-level for innovative projects
- Aligning Al efforts with business objectives and priorities

Transformational

- Endorsement and dedicated budget within each line of business
- Function-specific data science teams with domain expertise, in addition to the centralized advanced analytics team
- Innovation and research teams

Access



The theme concerns the extent to which your organization recognizes data management as a key element to enable AI and the degree to which data scientists can share, discover, and reuse data and other ML assets.

Tactical Transformational Strategic Managing an enterprise data No asset sharing Discovering, sharing, and reusing warehouse datasets and Al assets Isolated data islands Defining and sharing a unified data Standardized ML feature stores and Building a data lake model datasets Centralized data and ML asset Encouraging contributions from across the organization management

Learn



The theme concerns the quality and scale of learning programs to upskill your staff, hire outside talent, and augment your data science and ML engineering staff with experienced partners.

Tactical

- Self-motivated, isolated learning using online resources
- Third parties cover the skills gap in the organization
- No hiring for ML skills

Strategic

- Hiring data science and ML skills
- Organizing structured continuous training
- Strategic partner selected to provide consulting and specialized knowledge

Transformational

- Learning by embedding data scientists to the business function teams
- Hiring data science and ML talent for innovation with industry expertise
- Partnering to innovate, co-create, and augment technical resources

Secure



The theme concerns the extent to which you understand and protect your data and ML services from unauthorized and inappropriate access, in addition to ensuring responsible and explainable Al.

Tactical

- Implementing private networks with primitive IAM accessed and managed by a dedicated team
- Ensuring privacy through sensitive data classification and obfuscation
- Enabling data protection through encryption

Strategic

- Implementing principle of least privilege
- Exploring explainable AI techniques
- Investing in establishing Al ethics

Transformational

- IAM continuously monitored and improved
- Considering Al safety and robustness
- Developing fair ML systems

Scale



The theme concerns the extent to which you use cloud-native ML services that scale with large amounts of data and large numbers of data processing and ML jobs, with reduced operational overhead.

Tactical Transformational Strategic Dedicated hardware for cost Utilizing a fully managed serverless, data Operating an integrated ML control warehouse for ad hoc querying and data experimentation and production platform exploration Working with a limited number of small datasets Utilizing fully managed serverless data Using specialized ML accelerators services for ingestion and processing (GPUs, TPUs) on demand Using fully managed serverless ML services Orchestrating end-to-end data and for training and prediction serving ML pipelines

Automate



The theme concerns the extent to which you are able to deploy, execute, and operate technology for data processing and ML pipelines in production efficiently, frequently, and reliably.

Tactical

- Ad hoc, manual data processing and ML model training and serving
- High-risk changes reviewed and deployed infrequently and manually

Strategic

- Automating (scheduled and event-driven) data pipelines
- Automating ML training and batch-prediction pipelines
- Managing logging, monitoring, and notifications

Transformational

- Implementing ML training pipelines with continuous integration and delivery
- Implementing ML prediction services with continuous integration and delivery
- Managing ML model registry, ML metadata, and ML artifacts

Next Steps

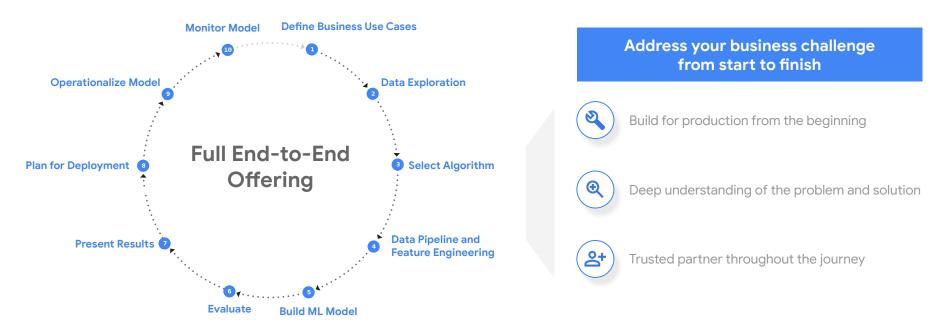
- Understand where you are complete the maturity assessment
- **Set your goal** where you do you want to go?
- Create a group of leaders who are responsible for building your AI capability?
- Devise a strategy based on the gaps, establish a plan for evolving your Al capability
- We are here to help you every step of the way speak to your account representative about how you can engage Google

Questions?

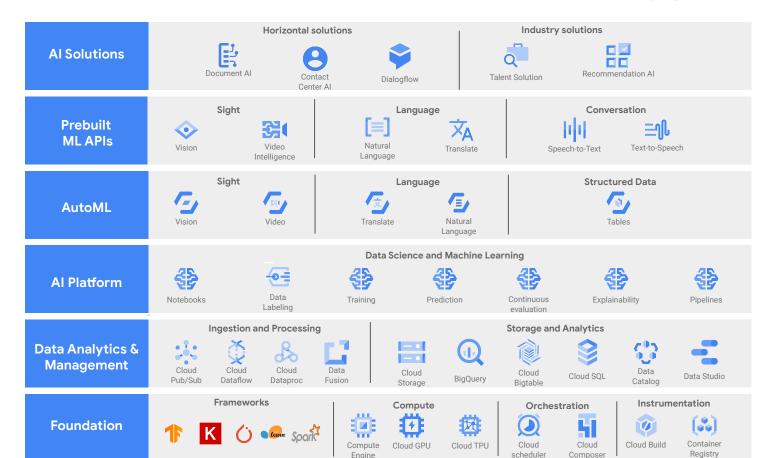
Appendix

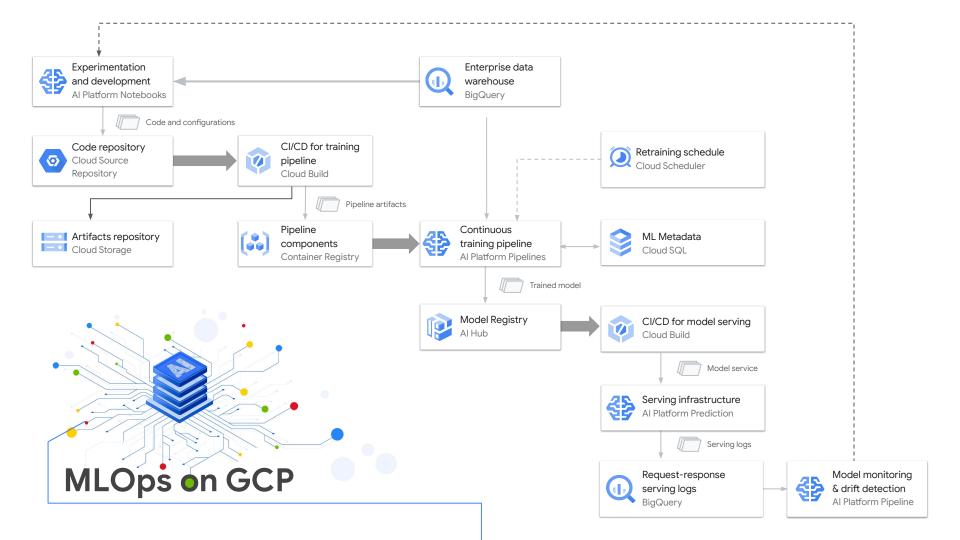
The transformational Al journey offering

Al Services provides a complete end-to-end path to accelerate your Al transformation



Google Cloud Smart Analytics & Al





ML Quality Control

• Testing in development

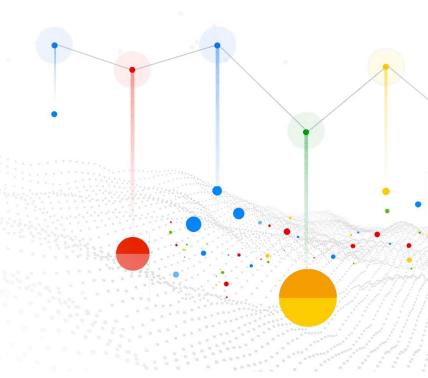
- Data and feature testing
- Model testing and debugging
- Model evaluation

• Testing in deployment

- Testing ML pipeline components integration
- ✓ Validate model-infrastructure compatibility
- Test model API

• Testing in production

- Pipeline data and model validation
- A/B testing and performance monitoring
- Data drift and shift detection





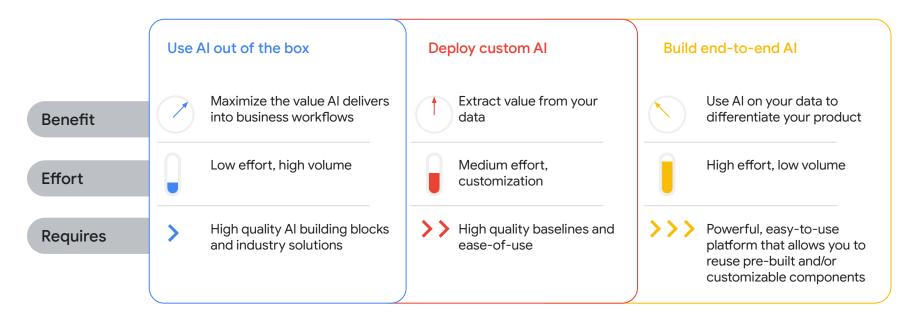
Machine Learning and MLOps on Google Cloud

Turan Bulmus Al/ML Practice Lead Benelux April 2022



Enable every company to be an Al company by reducing the challenges of Al model creation down to only the steps that require human judgement or creativity.

Build a portfolio of Al use cases



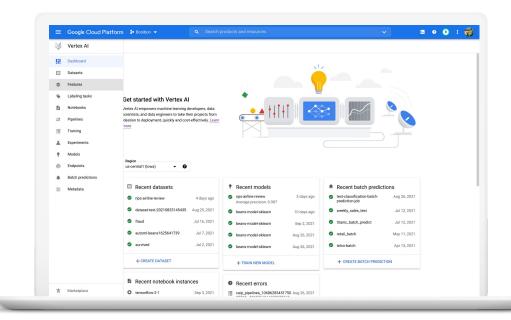
"Business value" generated from all three buckets Need a unified platform that supports all three buckets

A Unified ML Platform for Solving All Business Problems

Processing all sources of data including images, documents, tables, video



- One unified experience to create, deploy, and manage models over time, at scale
- Tools for all levels of expertise and for all types of data
- Accuracy and fairness of predictions and resulting decisions
- Flexible and secure

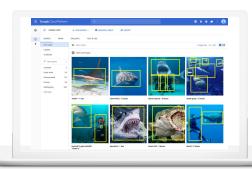


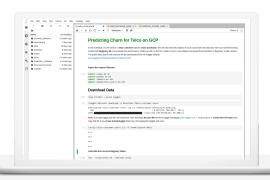


How to design your ML workflow?

Freedom of choice from no/low code to custom code







BigQuery ML

- Descriptive and predictive modeling on structured data
- Hyper-parameter tuning
- Feature engineering
- Explainability
- Simple SQL code

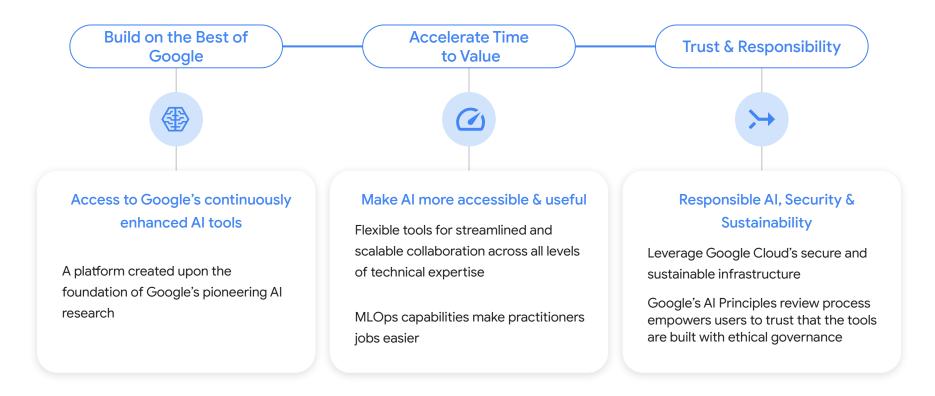
AutoML Models in Vertex Al

- Predictive modeling on structured & unstructured data
- Hyper-parameter tuning
- Feature engineering
- Explainability
- No code

End-to-end AI with Vertex AI

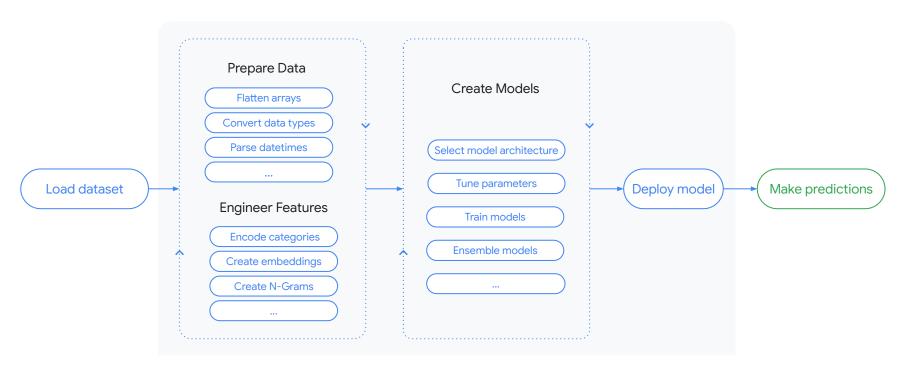
- Custom models on pre-built frameworks
- Noops, serverless training with hyperparameter tuning
- Explainability
- Custom code

Why organizations choose Vertex Al



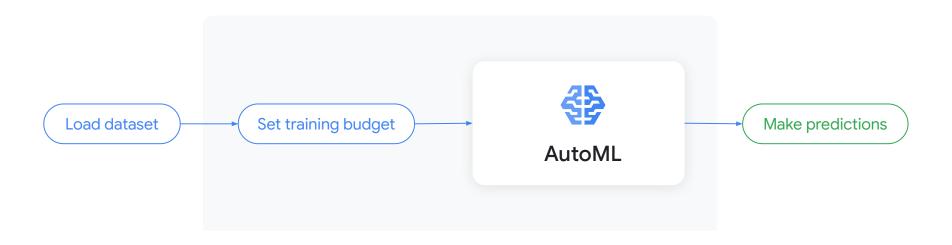
AutoML - Fastest path from data to value

Traditional Machine Learning Workflow



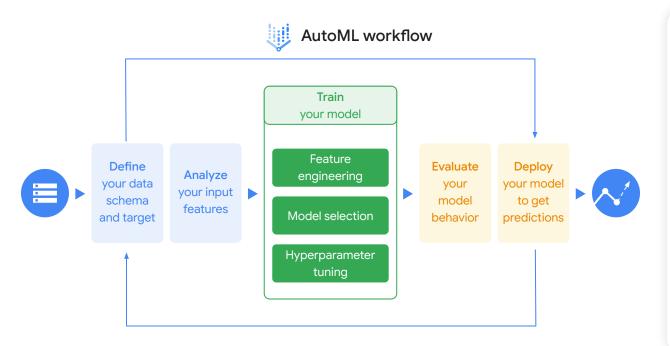
AutoML - Fastest path from data to value

AutoML Workflow



Low/No code

Point and click to build custom, high-quality models using the AutoML workflow in Vertex Al



Automatically search through Google's whole model zoo...

Linear, logistic

Feedforward DNN

Wide and Deep NN

Gradient Boosted Decision Tree (GBDT)

DNN + GBDT Hybrid

Adanet ensemble

Neural + Tree Architecture Search

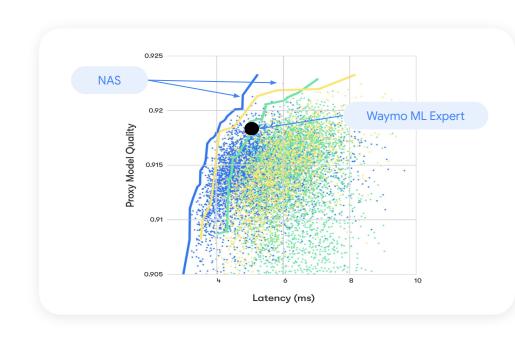
...and more!

Access to Google's best-in-class algorithms like NAS

Use of Neural Architecture Search (NAS) at Waymo

"Going from months of engineering time to generate and fine tune a architecture manually to "automatically generating" neural nets with NAS"

- © 20-30% lower latency/same quality
- 8–10% lower error rate/same latency
- NAS model in 2 weeks vs months (1 year of GPU time) searching over 10k architectures



MLOps

A set of **standardized** processes and technology capabilities for building, deploying, and operationalizing ML systems **rapidly** and **reliably**



Applications

Vision and Video (

Conversation

Language

Structured Data

Custom machine learning

Workbench

AutoML

NAS

Prediction

ML Metadata

Data Labeling

Training

Explainable Al

Feature Store

Model Monitoring

Experiments

Vizier (Optimization)

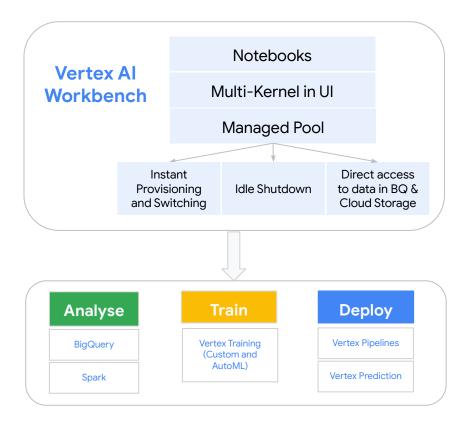
Pipelines

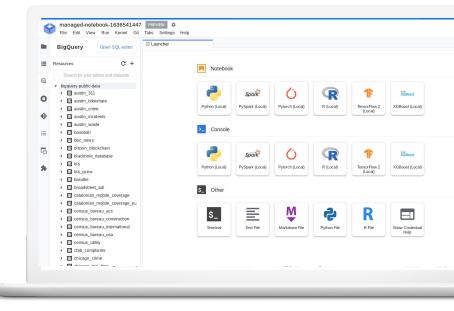
Matching Engine

Al Accelerators

Vertex Al Workbench with Managed Notebooks

A one-stop interface for Data Science

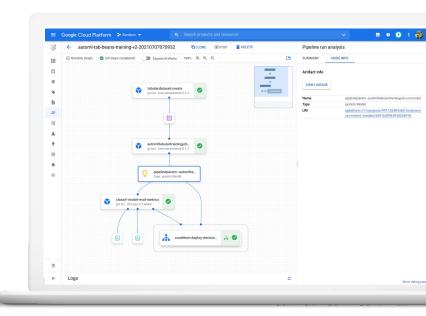




Vertex Pipelines

Automate, monitor, and govern your ML systems by orchestrating your ML workflow in a serverless manner, and storing your workflow's artifacts using Vertex ML Metadata

- Easy to use Python SDKs: Build your Pipelines using the battle-tested and easy-to-use KFP SDK and TFX SDK
- Scalable: Run as many pipelines on as much data as you want without having to worry about compute resources
- **Cost-effective:** Pay for the pipelines you run and the resources they use.
- Secure: Integrated with GCP security features like IAM, VPC-SC, and CMEK.
- Metadata Tracking and Lineage: Automatically store metadata about every artifact produced by the Pipelines.

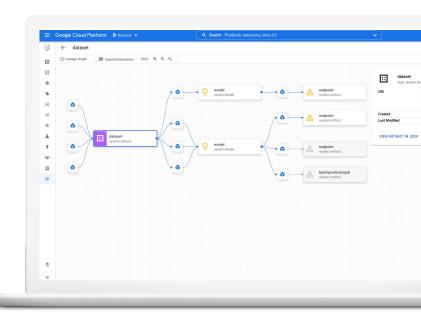




Metadata and Lineage on Vertex Al

Artifact, lineage, and execution tracking for your ML workflow

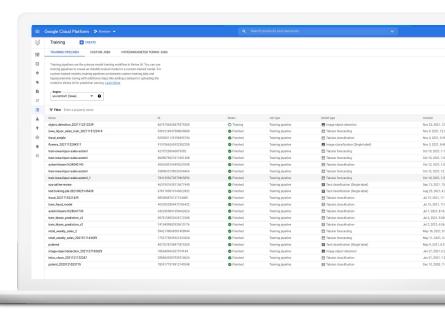
- Automatically track inputs and outputs to all components in an ML pipeline, and their lineage.
- Visualize the workflow for faster debugging with a DAG of all related executions.
- Manage artifacts by projects, group by experiments, and track the usage of datasets and models in your organization



Vertex Training

Artifact, lineage, and execution tracking for ML workflows, with an easy-to-use Python SDK.

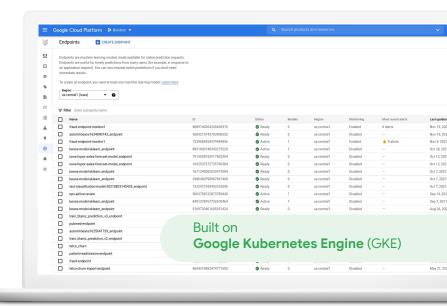
- Fully Managed: Train without provisioning or managing servers. Pay only for the compute you consume. Zero administration.
- High Performance: Optimized for Machine Learning.
 Scalable distributed orchestration with the most advanced cloud Accelerators (GPUs and TPUs)
- HyperParameter Optimization: Automatically tune models with Google's Vizier optimizer
- Customizable: Supports predefined (Tensorflow, Sklearn, XGB, Keras) and custom containers with flexible machines
- Built-in logging and monitoring: review your execution jobs and monitor resources utilization for your jobs





Vertex Prediction

- Serve online endpoints for low-latency predictions, or predictions on massive batches of data.
- Built-in security and compliance: VPC peering and security perimeter. Custom managed encryption keys. Fine-tuned access control.
- Low TCO: Scale automatically based on your traffic, and alleviate operational overhead.
- Intelligent and assistive: Built-in Model Explainability and proactive model monitoring.
- Log prediction requests and responses to BigQuery for monitoring and debugging
- Fast inference on GPUs: Support for a broad range of machine types specialized for ML, such as GPUs.

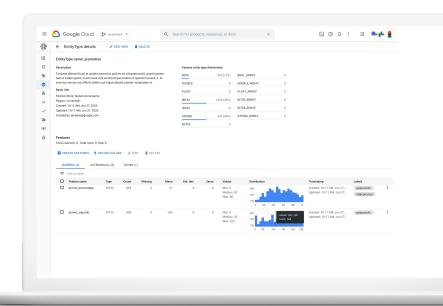


Feature Store on Vertex Al

A rich feature repository to serve, share and re-use ML features.

- Share and reuse ML features across use cases

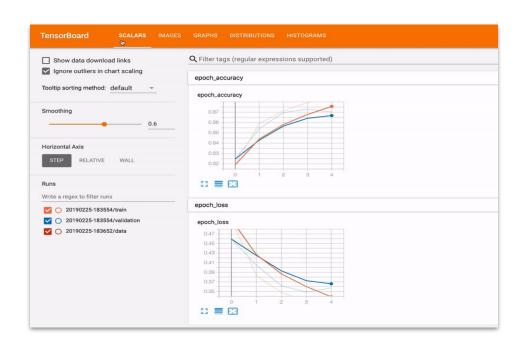
 Centralized feature repository with easy APIs to search & discover features, fetch them for training/serving and manage permissions.
- Offload the operational overhead of handling infrastructure for low latency scalable feature serving.
- Alleviate training serving skew
 - Compute feature values once, re-use for training and serving
 - Track & monitor for drift and other quality issues



TensorBoard: ML visualization toolkit

TensorBoard provides the visualization and tooling needed for ML experimentation

- Tracking and visualizing metrics such as loss and accuracy
- Visualizing the model graph (ops and layers)
- Viewing histograms of weights, biases, or other tensors as they change over time
- Projecting embeddings to a lower dimensional space
- Displaying images, text, and audio data
- Profiling TensorFlow programs



Get started with TensorBoard Docs

Explainable AI tells you how important each input feature is



Explanations tell you:

What **image pixels or regions** most contributed to the model's classification?

How much did each **feature column** contribute to a single prediction or the model overall?

How much did each **word** or **token** contribute to the text classification?

Explainable AI in AutoML, BQML and Vertex Prediction



Integrated in AutoML, BQML, Vertex Prediction and Custom Containers, enabling explanations and "feature attributions" for any prediction, both local and global.

Pre-installed in Vertex Workbench TensorFlow instances for rapid, local prototyping and analysis



Use What-if Tool in Vertex Al Notebooks to visualize explanations on tabular data and LIT (Language Interpretability Tool) on text and image data.

Enables interactive model evaluation, counterfactual explainability, and fairness analysis

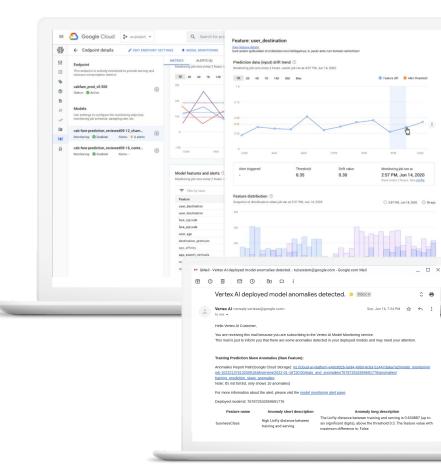
Monitoring of model performance

For models deployed in the Vertex Prediction service

and alert when those signals deviate.

- Monitor and alertMonitor signals for model's predictive performance,
- Diagnose

 Help identify the cause for the deviation i.e. what changed, how and how much?
- Trigger model re-training pipeline or collect relevant training data to address performance degradation.



New ML Tools on Vertex Al: Matching Engine

30-50% cheaper than alternatives, while delivering higher scale and lower latencies.

Faster i.e. low latency

Find nearest neighbors in a few millisecond

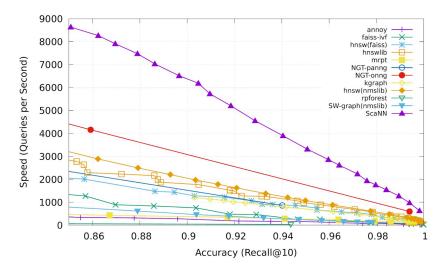
The most scalable

Scales to billions of vectors

Cheaper

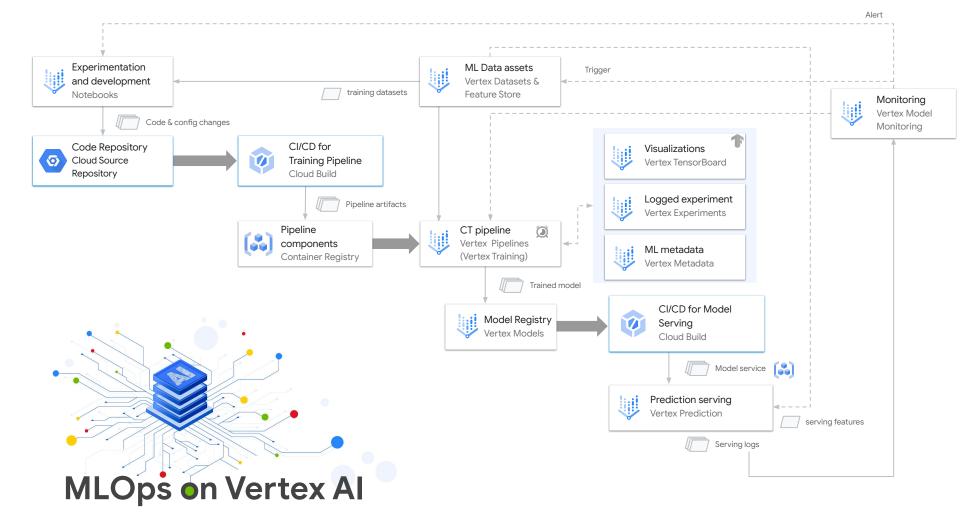
Requires fewer VMs to serve the same workload

- 1/4th the CPU consumption of faiss
- 1/3rd the memory consumption of **nmslib**



Google's technology (labelled **ScaNN**) compared with popular ANN services

Demo link
Google Cloud



Demo's Marijn

Data & Al







