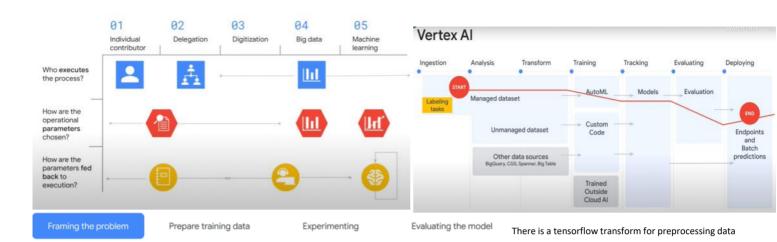
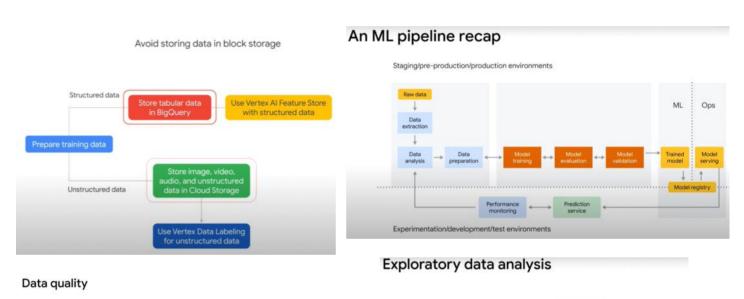
BASIC TUT

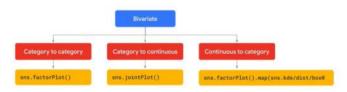
Thursday, October 27, 2022

6:58 PM







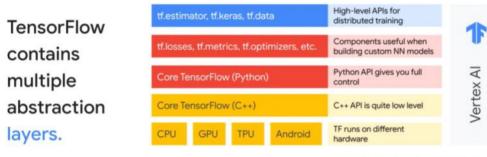


Wednesday, November 2, 2022 2:42 PM

A tensor is a N dimensional array of data

- Rank 0 tensor(scalar) (tf.constant(3)
- Rank 1 tensor (vector) (tf.constant([3,5,7]))
- Rank 2 tensor (matrix)
- Rank 3 tensor ()
- Rank 4 tensor ()

Tensorflow lite allows us to put the model trained into our mobile device and run inference or predictions offline



Run TF at scale with Al Platform.

Tf.constant produces constant tensors
Tf.Variable produces tensors that ca be modified

Tf.data.dataset allows us to

- Preporcess data in parallel (and cache result of costly operations)
- Configure the way the data is fed into a model with a number of chaining methods
- Create data pipelines form inmemory or out of memory sharded data files

Discretization:

- Turns continuous numerical features into bucket data with discrete ranges

Normalization:

- Holds the mean and standard deviation of the features

TextVectorization:

- Holds a mapping between string tokens and integer indices

Tf.keras.layers.Hashing:

- Performs categorical feature hashing

Tf.keras.layers.StringLookup:

- Turns string categorical values into an encoded representation that can be read by an embedding layer or dense layer

Tf.keras.layers.IntegerLookup:

- Turns integer categorical values into an encoded rep that can be read by an embedding layer or dense layer

FEATURE STORE

Monday, November 7, 2022 4:33 PM

- Feature store is a top level container for features and their values
- Permitted users can add and share their features and also users can ingest values from various data sources
- An Entity type is a collection of semantically related features
- An entity is an instance of an entity type
 Movie1,movie2 are entities of the movies entity type (entity should be an unique string)
- When we retrieve values from a feature store, the service returns an entity view that contains feature values that we requested
- 1) Batch serving
- High throughput, large volumes of data for offline processing
- 2) Online serving
- Low latency data retrive of small batches pf data for online real time processing

Pre requisites for feature store creation:

- No missing values
- Correct data type
- One hot encoding already done
- Include a column entity ID's, and the values to be string
- Source data must match the value types of the destination feature in the featurestore
- If providing feature generation timestamps choose TIMESTAMP type for bigquery,long,logical type for avro, rfc 3339 type for csv
- For array datatypes don't use csv and ain array instead of null value give an empty array

First Featurestore is created and entity type is created and features(fields in the dataset) are added to the entity type with its feature name type etc..

Csv, tfrecord format is usd for batch serving outputs

Feature columns:

- Numerical
- Categorical
- Bucketized
- Crossed
- Embedding
- Hashed

Features should be known at prediction time Features should be numeric Features should have enough examples

Feature engineering:

- Representation transformation:
 - Convert a numeric feature to a categorical feature(bucketization)
 - Convert categorical features to a numeric representation (one hot encoding, feature embeddings etc..)
- Feature construction
 - Create new features either by using typical techniques (polynomial expansion by using univariate mathematical funcs or feature crossing)
 - A feature cross is a synthetic feature formed by multiplying (crossing) two or more

features. Crossing combinations of features can provide predictive abilities beyond what those features can provide individually

TRANSFORM(ML.FEATURE_CROSS(STRUCT(features)),ML.BUCKETIZE(feature,splitpoints(array)) etc..)

Bucketnames has the name bin and it will be with the feature values

Machine Learning in the Enterprise

Tuesday, November 8, 2022 10:00 AM

Making training faster:

- Use tpu's
- Making an input pipeline faster
- Running parallely in many devices in tpu's,gpu's etc..
- Distributed processing with multiple machines with multiple devices in parallel
- Use Data parallellism

Data parallelism:

- Use many workers and have their own data for training
- Update model parameters for the synchronization of the model (for combining results like)
- There will be a async parameter server for all the workers that syncs the parameters(choose if many low power or unreliable workers)
- There is also a sync allreduce parameter server that will synchronize the parameters form the parent worker to the child worker without the need of a central parameter server for all the workers(choose if multiple devices on one host)

Model parallelism:

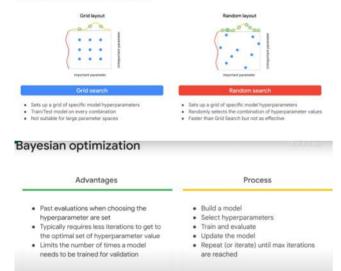
- Putting different devices on different layers of deeplearning

Maximum artifact size for custom training is like 5 tb

Vizier hyperparameter tuning:

- Grid search
- Random search
- Bayesian optimization(default)

Grid and Random Search



While creating a model custom training and give custom image and in the hyperparameters page click enable hyperparameter tuning and give the hyperparameters that matches with the command line args in your code

We can set a maximum number of trials and max no of parallel trials(lower than max trials)

Predictions:

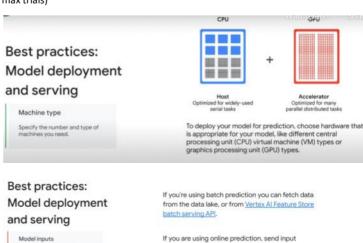
- Batch prediction is asynchronous
- Online prediction is synchronous

Best practices:

Model deployment and serving



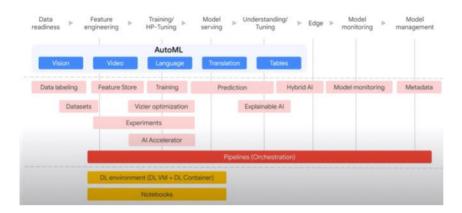




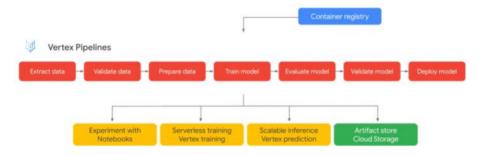
instances to the service and it returns your predictions in the response.

in model monitoring use skew detection, drift detection For seeing changes to produuction data in accordance with training

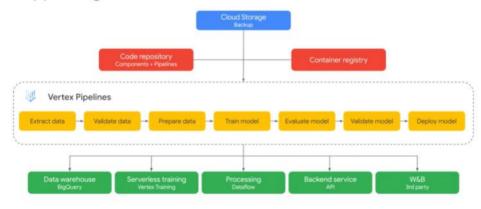
Use alert threshold



Pipelines automate the training and deployment of models

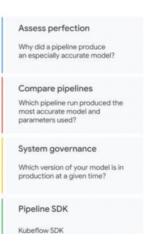


Supporting architecture



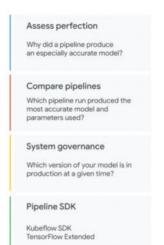
Best practices: Vertex AI Pipelines





Best practices: Vertex Al Pipelines





Artifact lineage describes all the factors that resulted in an artifact.

You can understand differences in performance or accuracy over several pipeline runs.

Best practices: Artifact organization

A model's lineage could include the following:

- The training, test, and evaluation data used to create the model.
- · The hyperparameters used during model training.
- The code that was used to train the model.
- Metadata recorded from the training and evaluation process.
- · Artifacts that descend from this model.

Best practices: Artifact organization

latch later Sha



Artifacts are outputs resulting from each step in the ML workflow.

Artifacts
Organize your
ML model artifacts.

Git repo
Use a Git repo for pipeline definitions and training code.

Production Machine Learning System

Tuesday, November 8, 2022 8:54 P

- For all non numeric columns , other than TIMESTAMP, bigquery ML performs a one hot encoding transformation

RECOMMENDATION SYSTEMS:

- Content based
- Collaborative filtering

Content based filtering uses item features to recommend new items that are similar to what the user has liked in the past

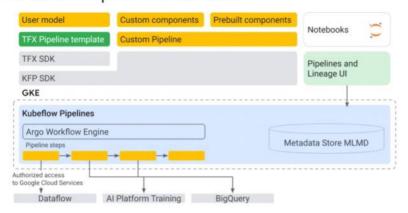
Current process for building an MLOps pipelin

- Set up a Google Kubernetes Engine (GKE) cluster.
- Create a Cloud Storage bucket for storing data.
- Install Kubeflow pipelines.
- · Set up port forwarding.
- Create a process to share the pipeline with your team.

Al platform pipelines automates it

- 2. Easy authentication process
 - Fully secure and provides authenticated access to Pipelines UI
 - · No need to set up port forwarding
 - · Easy to share with team members
 - Easy to access through REST API service
 - Seamless performance of using Pipelines SDK from Notebooks
 - Define pipeline
 - o Schedule run job

Al Platform Pipelines tech stack

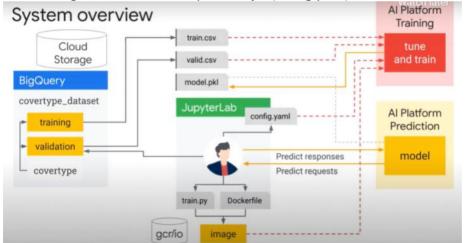


Al Platform Pipelines implementation strategy

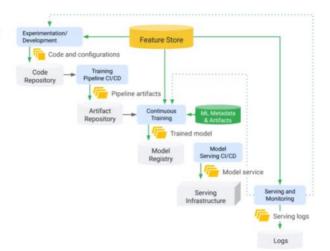
Kubeflow Pipelines TensorFlow Extended (TFX) Through Kubeflow Pipelines SDK Through TFX SDK · Lower-level ML framework-agnostic · Higher-level abstraction implementation · Prescriptive but customizable · Enables direct control of Kubernetes components with pre-defined ML types resource control · Brings Google best practices for · Simple sharing of containerized robust/scalable ML workloads components • Use it for E2E TF-based pipeline with customizable data pre-processing · Use it for fully custom pipelines and training code

Building and operationalizing models:

- Implement a tunable training application(train.py)
- Package your training application(Dockerfile)
- Configure and start and ai platform job(config.yaml)



Where we are going next



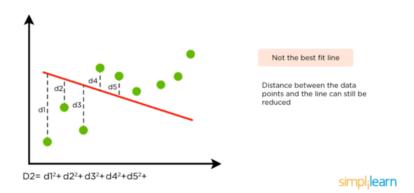
For splitting the dataset into training and test dataset we can use hashing and mod combined when querying the data like MOD(ABS(FARM_FINGERPRINT(FIELD),8) < 8
Or if we are not sure what to hash on we can use TO_JSON_STRING(tablename) inside the farm_fingerprint()

In code we can use fire python package for accepting cli args in function

Import fire
Def fucn(col1,col2):
Pass
Fire.Fire(func)
(python train.py --col1=dd --col2=cc)

Linear Regression

Finding the best fit line: The best fit line can be found out by minimizing the distance between all the data points and the distance to the regression line. Ways to minimize this distance are sum of squared errors, sum of absolute errors etc.



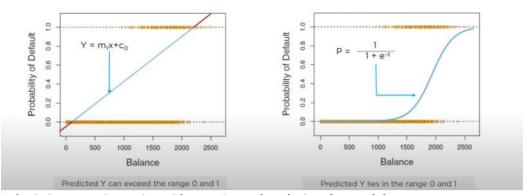
The regression line is drawn randomly and the distance between the line and the each data points summed together

Should be less (sum of squared error)

Internally the code tried to get the line close to the data points that result to a less squared error Cost function says how far the line is from the data points

Logistic Regression

Plotting the Logistic Regression Curve: The Logistic Regression curve is known as the Sigmoid curve (S curve)



In logistic regression a sigmoid curve is used to design the model