

Requirements and Solutions Document for Leveraging Embeddings with NVTabular Workflows for Training and Deployment

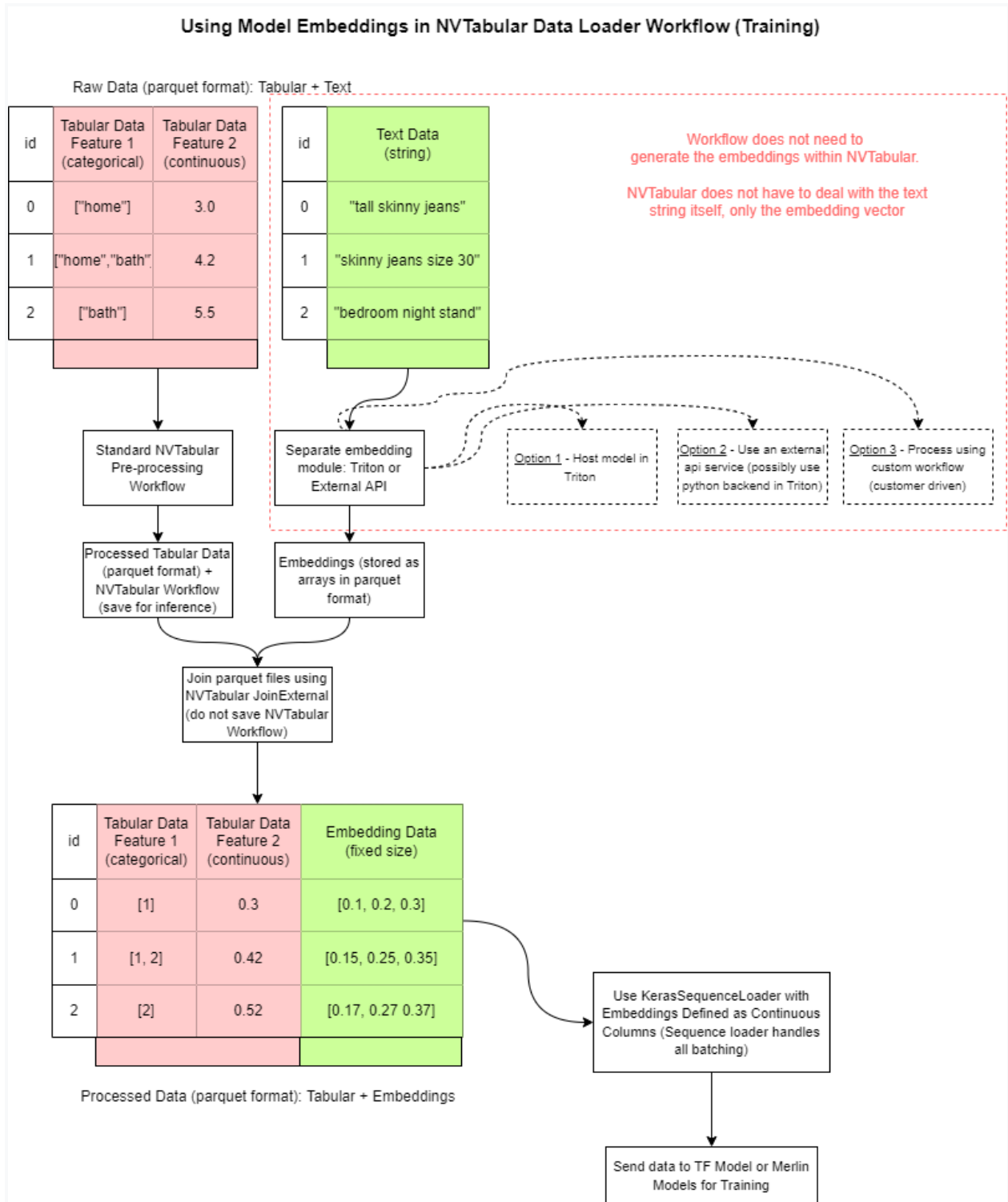
Objective

- Leverage dense vectors/embeddings as model inputs that were obtained from an encoder model (text, image, other) for raw input data (text, image, etc) and leverage these embeddings in NVTabular data loaders during training and inference workloads for RecSys models (including Transformers4Rec)
- Benefits
 - model based embeddings can be generated for all possible entities, which might not be in the training set.
 - model based embeddings can be trained on one task and used on another task, with or without further tuning.
 - With the embeddings as an input feature vector, the number of parameters are reduced compared with learning the embeddings during task training.
 - Workflow may be used in general RecSys models (ideally Merlin Models) along with Transformers4Rec (some alteration may be required)
 - Leverage the speed of GPU processing to complete this workload in fastest time possible

Assumptions

- All input data (of Tabular format) during training should be fetched by the NVTabular Data Loader to optimize training times (through faster data loading)
 - If tabular data is fetched by NVTabular and other data is fetched by the underlying framework (FW - Tensorflow or Pytorch), then coordinating batches of data from two different fetches can be complicated and potentially reduce data loading speeds
- NVTabular as a feature engineering module is not able to host a model (or make a call to an external model service) in its current state
- NVTabular does not have to process the raw input string, just be able to work with the embedding inputs that come from some other text encoding process.
- The workflow for training can be different to the workflow for inference

Using Model Embeddings in NVTabular Data Loader Workflow (Training)



Using encoder (embedding generator) + NVTabular Workflow in Triton ()

