TechyEdz Solutions

Training | Consulting | Developement | Outsourcing

GCP Professional Machine Learning Engineer

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GCP Professional Machine Learning Engineer

Course Overview:

A Professional Machine Learning Engineer designs, builds, and productionizes ML models to solve business challenges using Google Cloud technologies and knowledge of proven ML models and techniques. The ML Engineer is proficient in all aspects of model architecture, data pipeline interaction, and metrics interpretation and needs familiarity with application development, infrastructure management, data engineering, and security.

Course Outline:

1: ML Problem Framing

1.1 Translate business challenge into ML use case

- Defining business problems
- Identifying nonML solutions
- Defining output use
- Managing incorrect results
- Identifying data sources

1.2 Define ML problem

- Defining problem type (classification, regression, clustering, etc.)
- Defining outcome of model predictions
- Defining the input (features) and predicted output format

1.3 Define business success criteria

- Success metrics

- Key results
- Determination of when a model is deemed unsuccessful

1.4 Identify risks to feasibility and implementation of ML solution

- Assessing and communicating business impact
- Assessing ML solution readiness
- Assessing data readiness
- Aligning with Google AI principles and practices (e.g. different biases)

2: ML Solution Architecture

2.1 Design reliable, scalable, highly available ML solutions

- Optimizing data use and storage
- Data connections
- Automation of data preparation and model training/deployment
- SDLC best practices

2.2 Choose appropriate Google Cloud software components

- A variety of component types - data collection; data management
- Exploration/analysis
- Feature engineering
- Logging/management
- Automation
- Monitoring
- Serving

2.3 Choose appropriate Google Cloud hardware components

- Selection of quotas and compute/accelerators with components

2.4 Design architecture that complies with regulatory and security concerns

- Building secure ML systems
- Privacy implications of data usage
- Identifying potential regulatory issues

3: Data Preparation and Processing

3.1 Data ingestion

- Ingestion of various file types (e.g. Csv, json, img, parquet or databases, Hadoop/Spark)
- Database migration
- Streaming data (e.g. from IoT devices)

3.2 Data exploration (EDA)

- Visualization
- Statistical fundamentals at scale
- Evaluation of data quality and feasibility

3.3 Design data pipelines

- Batching and streaming data pipelines at scale
- Data privacy and compliance
- Monitoring/changing deployed pipelines

3.4 Build data pipelines

- Data validation
- Handling missing data
- Handling outliers
- Managing large samples (TFRecords)
- Transformations (TensorFlow Transform)

3.5 Feature engineering

- Data leakage and augmentation
- Encoding structured data types
- Feature selection
- Class imbalance
- Feature crosses

4: ML Model Development

4.1 Build a model

- Choice of framework and model
- Modeling techniques given interpretability requirements
- Transfer learning
- Model generalization
- Overfitting

4.2 Train a model

- Productionizing
- Training a model as a job in different environments
- Tracking metrics during training
- Retraining/redeployment evaluation

4.3 Test a model

- Unit tests for model training and serving
- Model performance against baselines, simpler models, and across the time dimension
- Model explainability on Cloud AI Platform

4.4 Scale model training and serving

- Distributed training
- Hardware accelerators
- Scalable model analysis (e.g. Cloud Storage output files, Dataflow, BigQuery, Google Data Studio)

5: ML Pipeline Automation & Orchestration

5.1 Design pipeline

- Identification of components, parameters, triggers, and compute needs
- Orchestration framework

- Hybrid or multi-cloud strategies

5.2 Implement training pipeline

- Decoupling components with Cloud Build
- Constructing and testing of parameterized pipeline definition in SDK
- Tuning compute performance
- Performing data validation
- Storing data and generated artifacts

5.3 Implement serving pipeline

- Model binary options
- Google Cloud serving options
- Testing for target performance
- Setup of trigger and pipeline schedule

5.4 Track and audit metadata

- Organization and tracking experiments and pipeline runs
- Hooking into model and dataset versioning
- Model/dataset lineage

5.5 Use CI/CD to test and deploy models

- Hooking modes into existing CI/CD deployment system
- AB and Canary testing

6: ML Solution Monitoring, Optimization, and Maintenance

6.1 Monitor ML solutions

- Performance and business quality of ML model predictions
- Logging strategies
- Establishing continuous evaluation metrics

6.2 Troubleshoot ML solutions

- Permission issues (IAM)

- Common training and serving errors (TensorFlow)
- ML system failure and biases

6.3 Tune performance of ML solutions for training & serving in production

- Optimization and simplification of input pipeline for training
- Simplification techniques
- Identification of appropriate retraining policy

- **Prerequisites: None**

- **Who Should Attend:**
- 3+ years of industry experience including 1+ years designing and managing solutions using GCP.

- **Number of Hours: 40hrs**

- **Certification: GCP Professional Machine Learning Engineer (GCP MLE)**

- **Key Features:**
- One to One Training
- Online Training
- Fastrack & Normal Track
- Resume Modification
- Mock Interviews
- Video Tutorials
- Training Materials
- Real Time Projects
- Virtual Live Experience
- Preparing for Certification
- Life time Access