Back To Module Home

Machine Learning System Design

0% completed

Machine Learning Primer

- Introduction
- Feature Selection and Feature Engineering
- Training Pipeline
- Inference
- Metrics Evaluation

Video Recommendation

Feed Ranking

Ad Click Prediction

Rental Search Ranking

Estimate Food Delivery Time

Machine Learning Knowledge

Machine Learning Model Diagnosis

Conclusion

Mark Module as Completed

Training Pipeline

Learn common requirements and patterns in building training pipelines.

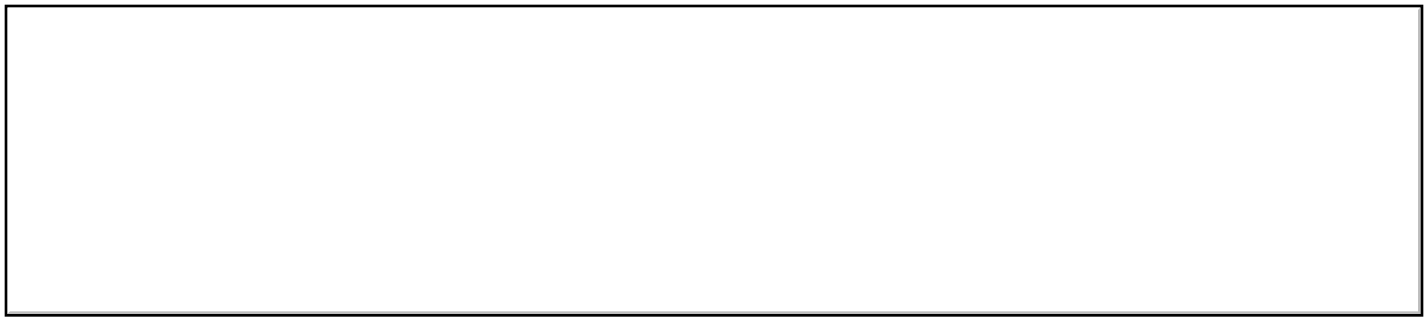
We'll cover the following

Training pipeline#

A training pipeline needs to handle a large volume of data with low costs. One common solution is to store data in a column-oriented format like Parquet or ORC. These data formats enable high throughput for ML and analytics use cases. In other use cases, the tfrecord data format is widely used in the TensorFlow ecosystem.

Data partitioning#

- Parquet and ORC files usually get partitioned by time for efficiency as we can avoid scanning through the whole dataset. In this example, we partition data by year then by month. In practice, most common services on AWS, RedShift, and Athena support Parquet and ORC. In comparison to other formats like csv, Parquet can speed up the query times to be 30x faster, save 99% of the cost, and reduce the data that is scanned by 99%.



Partition training data in Parquet format

Handle imbalance class distribution#

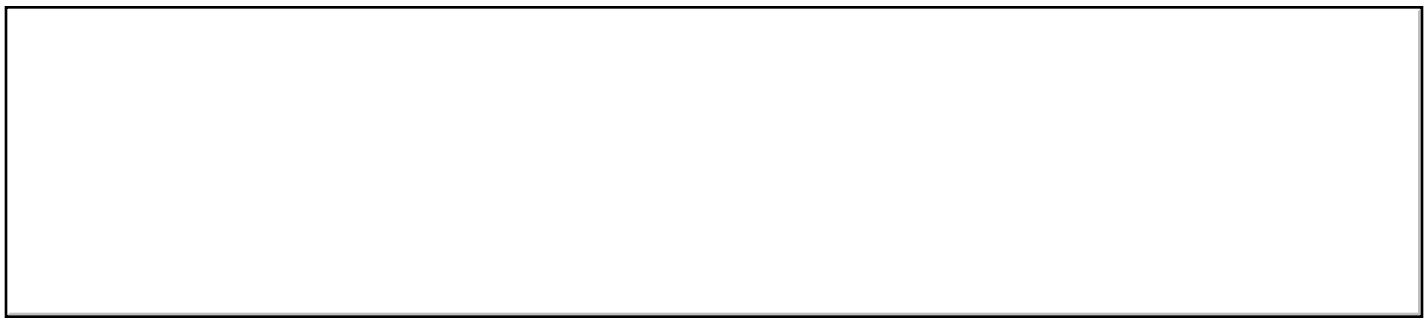
In ML use cases like Fraud Detection, Click Prediction, or Spam Detection, it's common to have imbalance labels. There are few strategies to handle them, i.e, you can use any of these strategies depend on your use case.

- Use **class weights in loss function**: For example, in a spam detection problem where non-spam data has 95% data compare to other spam data which has only 5%. We want to penalize more in the non-spam class. In this case, we can modify the entropy loss function using weight.

```
//w0 is weight for class 0,
w1 is weight for class 1
```

```
loss_function = -w0 *
ylog(p) - w1*(1-y)*log(1-p)
```

- Use **naive resampling**: Resample the non-spam class at a certain rate to reduce the imbalance in the training set. It's important to have validation data and test data intact (no resampling).
- Use **synthetic resampling**: The Synthetic Minority Oversampling Technique (SMOTE) consists of synthesizing elements for the minority class, based on those that already exist. It works by randomly picking a point from the minority class and computing the k-nearest neighbors for that point. The synthetic points are added between the chosen point and its neighbors. For practical reasons, SMOTE is not as widely used as other methods.



Choose the right loss function#

- It depends on the use case when deciding which loss function to use. For binary classification, the most popular is `cross-entropy`. In the Click Through Rate **(CTR)** prediction, Facebook uses Normalized Cross Entropy loss (a.k.a. `logloss`) to make the loss less sensitive to the background conversion rate.
- In a forecast problem, the most common metrics are the Mean Absolute Percentage Error (MAPE) and the Symmetric Absolute Percentage Error (SMAPE). For MAPE, you need to pay attention to whether or not your target value is skew, i.e., either too big or too small. On the other hand, SMAPE is not symmetric, as it treats under-forecast and over-forecast differently.

Mean Absolute Percentage Error

$$M = \frac{1}{n}\sum_{t=1}^{n}\left[\frac{A_t - F_t}{A_t}\right]$$

Symmetric Absolute Percentage Error

$$SMAPE = \frac{100\%}{n}\sum_{t=1}^{n}\frac{[F_t - A_t]}{([A_t]+[F_t])/2}$$

M = mean absolute percentage error

n = number of data

A_t = actual value

F_t = forecast value

- Other companies also use Machine Learning and Deep Learning for forecast problems. For example, Uber uses many different algorithms like Recurrent Neural Networks(RNNs), Gradient Boosting Trees, and Support Vector Regressors for various problems.

Some of the problems include Marketplace forecasting, Hardware capacity planning, and Marketing.

- For the regression problem, DoorDash used Quantile Loss to forecast Food Delivery demand.
- The Quantile Loss is given by:

$$L(\hat{y}, y) = max(\alpha(\hat{y} - y), (1 - \alpha)(y - \hat{y}))$$

Retraining requirements#

- Retraining is a requirement in many tech companies. In practice, the data distribution is a non-stationary process, so the model does not perform well without retraining.
- In AdTech and recommendation/personalization use cases, it's important to retrain

models to capture changes in user's behavior and trending topics. So, machine learning engineers need to make the training pipeline run fast and scale well with big data. When you design such a system, you need to balance between model complexity and training time.

- A common design pattern is to use a **scheduler** to retrain models on a regular basis, usually many times per day.

Quiz on Logloss

1

Compute the Categorical cross-entropy metric for this classifier

Actual label

	Apple	**Pear**	**Orange**
sample 1	1	0	0
sample 2	1	0	0
sample 3	1	0	0

	pApple	**pPear**	**pOrange**
sample 1	0.7	0.15	0.15
sample 2	0.7	0.15	0.15
sample 3	0.33	0.33	0.34

Question 1 of 4

0 attempted

What scheduler softwares/tools can be used for retraining models?

Feature Selection and Feature Engin…

Next

Inference

Mark as Completed

Report an Issue