# Dynamic Graph Sampling Service for Real-time GNN Inference at Scale

Jie Sun† Li Su‡ Wenting Shen‡ Zichao Zhang‡ Zuocheng Shi† Jingbo Xu‡
Yong Li‡ Wenyuan Yu‡ Zeke Wang† Fei Wu† Jingren Zhou‡
Zhejiang University† Alibaba Group‡

## Background

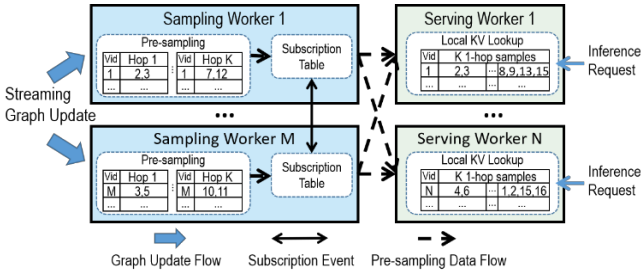
### GNN Inference Service on Dynamic Graph

In industrial GNN scenarios, sampling-based mini-batch training is widely adopted to scale out GNN applications to very large graphs, where receptive fields for vertices are obtained via neighbor sampling during both model training and inference.Since the structure and attributes of real-world graphs change continuously, it is imperative that the inferred vertex representation can accurately reflect these dynamic updates in real-time. GNN inference services on dynamic graph mush achieve latency-related SLOs. For example, GNN-based real-time recommendation systems often require stable millisecond-level latency performance.

## Challenges

(1) High time complexity of K-hop sampling;
(2) I/O overheads of distributed graph storage;
(3) Imbalanced workload due to graph skewness.

## System Overview




### Target:

Real-time GNN inference service on large-scale dynamic graph.

### Insights:

GNN inference service is query-aware.

### Architecture:

DGS decouples graph sampling and GNN inference physically.

**Sampling worker:** Each sampling worker is responsible for a specific graph partition: conducting pre-sampling for the decomposed one-hop sampling queries and delivering the sampling results to the serving workers.

**Serving worker:** Each serving worker caches the sampling results of K one-hop queries received from sampling workers and serves the inference requests for a partition of vertices in the graph.

DGS is open-sourced as a part of Graph-Learn:
https://github.com/alibaba/graph-learn

## Key Designs

### Sampling Worker

**Step 1: Decompose K-hop query into K 1-hop queries**

Example: 2-hop Query

```
g.V("user", feed_id).alias("seed")
  .OutV("click").sample(2).by("random")
  .OutV("swing").sample(2).by("random").values
```

Decomposed into:

1-hop query $Q_1$:

```
V.OutV("click").sample(2).by("random")
```

1-hop query $Q_2$:

```
V.OutV("swing").sample(2).by("random")
```

Exclusively store the 1 hop samples on sampling workers

**Step 2: Event-driven reservoir sample**

Graph update event: Edge_Type (src_v, dst_v, timestamp)

E.g., `click(1, 5, T1); swing(4, 8, T2)`

Reservoir sampling: Randomly replace existing samples

| Time | Vid | $Q_1$ | Vid | $Q_2$ | Updated? |
|---|---|---|---|---|---|
| $T_0$ | 1 | 2, 3 | 4 | 6, 7 | / |
| $T_1$ | 1 | 2, 5 | 4 | 6, 7 | yes |
| $T_2$ | 1 | 2, 5 | 4 | 6, 7 | no |

**Step 3: Update the subscription table**

Suppose vertex 3 is only sampled by vertex 1.

| Time | Hop | Vid | Subscribed by |
|---|---|---|---|
| $T_0$ | $Q_1$ | 1 | Serving worker 1 |
| $T_0$ | $Q_2$ | 3 | Serving worker 1 |
| $T_1$ | $Q_1$ | 1 | Serving worker 1 |
| $T_1$ | $Q_2$ | 5 | Serving worker 1 |

### Serving Worker

Handle inference request for a partition of vertices

Generate K-hop samples by local KV Lookups.

| Worker | Vid | $Q_1$ | $Q_2$ |
|---|---|---|---|
| 1 | 1 | 2, 5 | 8, 9, 10, 13 |

| Worker | Vid | $Q_1$ | $Q_2$ |
|---|---|---|---|
| 2 | 8 | 4, 9 | 6, 7, 15, 16 |

## Evaluation

### Settings:

(1) Real Alibaba e-commerce datasets, #V=240M, #E=6.1B;
(2) 2-hop random sampling query, fan-outs=[15,10];
(3) 2 machines for sampling workers, 2 machines for serving workers, each with 64 * Intel(R) Xeon(R) CPU E5-2682 v4, 256GB host memory, 960GB SAMSUNG NVMe SSD

### Results in a single machine:

| | |
|---|---|
| **Serving Latency** | P99: 20ms |
| **Serving Throughput** | 20,000 QPS |
| **Update Ingestion Throughput** | 109MB/s |

Serving & update ingestion throughput can scale out linearly.