User Guide

This document serves as a simple user guide for the GMNS data format version of Big data-driven Transportation Computational graph (BTCG) framework.

1. Introduction

BTCG (Wu et al., 2018) is a forward and backward propagation algorithmic framework on a layered computational graph, which can perform hierarchical travel demand estimation using multiple data sources. BTCG can be viewed as an implementation of conceptual Hierarchical Flow Networks (HFN). By applying the back propagation (BP) algorithm, one can view each variable as a vertex and the edge between vertexes to translate the calculation process between variables as a computational graph.

The specific relationship between the layers of HFN is shown in Fig 1., which covers the input/output variables of each layer and the relationship between layers.

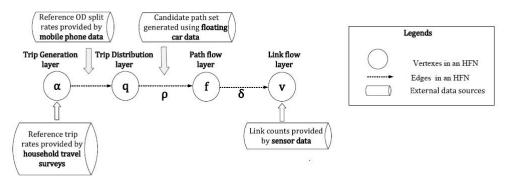


Fig. 1. HFN of Traffic Demand Flow Estimation (TDFE) model

To minimize the loss function, parameters such as α , π and θ are updated during the training process. Finally, the traffic flow of each layer (e.g., α of ozone layer, γ of OD layer, γ of link layer) are estimated jointly.

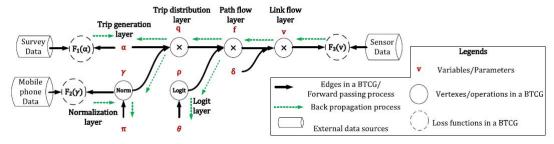


Fig. 2. Corresponding BTCG of HFN

2. Data flow

Input files	Output files		
node.csv	output_ozone.csv		
agent.csv	output_od.csv		
agent_type.csv	output_path.csv		
road_link.csv	output_link.csv		

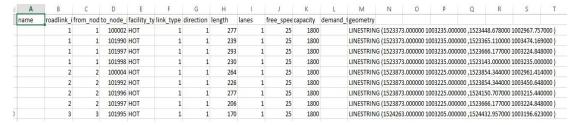
File node.csv

This file of node csv includes the basic node information about the test network, such as name,

node id, zone id, node type, ctrl type, x coord, y coord, and geometry.

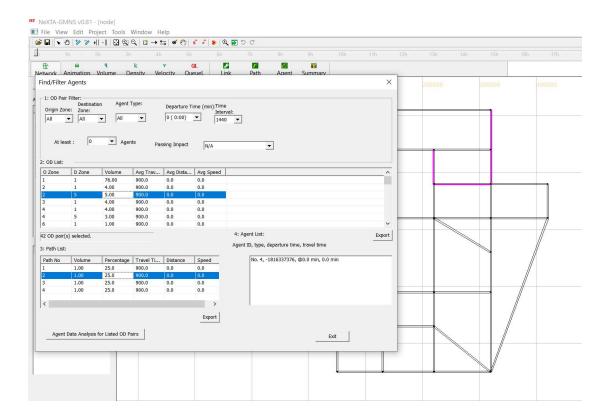
-4	Α	В	C	D	E	F	G	Н	1	J	K	L
1	name	node_id	zone_id	node_typ	ctrl_type	x_coord	y_coord	geometry				
2		1	0			1523373	1003235	POINT (15	23373.000	000 100323	35.000000)	
3		2	0			1523873	1003225	POINT (15	23873.000	000 100322	25.000000)	
4		3	0			1524263	1003205	POINT (15	24263.000	000 100320	05.000000)	
5		4	0			1524224	1002265	POINT (15	24224.000	000 100226	55.000000)	
6		5	0			1523854	1002765	POINT (15	23854.000	000 100276	55.000000)	
7		6	0			1523354	1002745	POINT (15	23354.000	000 100274	15.000000)	

road link.csv, which includes basic link-level information.



input agent.csv

There are different types of measurements stored in agent.csv, and one can use NeXTA to visualize the path trajectories.



Our source code considers an integration of multiple data sources, namely the household survey data (ozone data), the OD reference volume or the OD split rate (mobile phone data), the link count (sensor data), and the path information such as its node sequences.

4	Α	В	С	D	E	F	G	Н	1	J	K
1	agent_id	agent_type	from_zone_id	to_zone_id	from_node_id	to_node_id	od_flow	node_sequence	path_flow	time_peroid	observations
2	1	1	3	-1	3	-1	-1	-1	-1	1	70
3	2	1	12	-1	12	-1	-1	-1	-1	1	60
4	3	1	4	-1	4	-1	-1	-1	-1	1	90
5	4	1	6	-1	6	-1	-1	-1	-1	1	70
6	5	1	8	-1	8	-1	-1	-1	-1	1	30
7	6	1	9	-1	9	-1	-1	-1	-1	1	50
8	7	1	10	-1	10	-1	-1	-1	-1	1	60
9	8	1	11	-1	11	-1	-1	-1	-1	1	100
10	9	1	16	-1	16	-1	-1	-1	-1	1	90
11	10	1	2	-1	2	-1	-1	-1	-1	1	80
12	11	1	7	-1	7	-1	-1	-1	-1	1	50
13	12	1	18	-1	18	-1	-1	-1	-1	1	80

agent_type.csv

File agent_type.csv is used to specify the agent/information type in the measurements in input_agent.csv. Currently, we consider 4 information types: 1. household survey samples; 2. OD reference volume; 3. path proportions; 4. link counts. The field of "attribute 1" means the number of observations, and the field of "attribute 2" means the number of time periods. In our current implementation, we consider one day or peak period of traffic volume, thus the number of time periods is set to 1.

	А	В	С	D	E
1	agent_type_id	agent_type	attribute1	attribute2	
2	1	household survey	22	1	
3	2	od reference volume	33	1	
4	3	path proportion	126	1	
5	4	link count	76	1	
6					

3. Case study

As shown in Fig. 3, the illustrative Sioux Falls network is used as the test case, with 22 zones, 24 nodes, 33 OD pairs, 76 links and 132 paths. The GMNS format data set is provided in the sub folder of /SiouxFalls network.

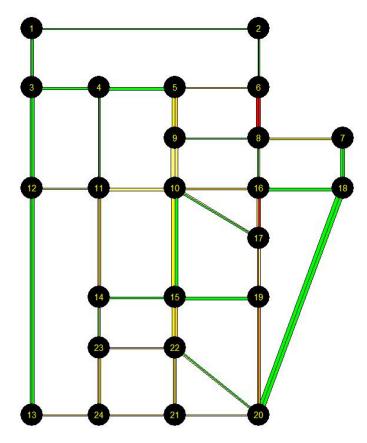
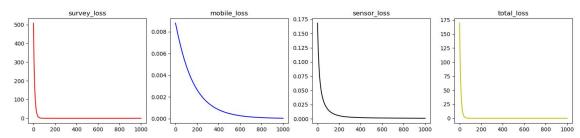


Fig. 3. Sioux Falls Network

Training results (1000 epochs):

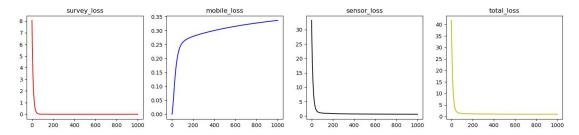
BTCGLite_GMNS.py. Tthis simplified version does not use the logit model and related class objects, to speed up the computational time.



step 1000 :survey error= 6.983434152935154e-08 step 1000 :mobile error= 3.8845606447143905e-05 step 1000 :sensor error= 0.0010404423796513053

step 1000 :total error= 0.0010792072388590332

BTCG_GMNS.py In this standard version with embedded non-convex logit functions, the loss associated with mobile data (i.e. OD splits) increases to a certain degree, but the total loss function has been reduced as a result of the optimization process performed by Tensorflow.



step 1000 :survey error= 3.1824046e-09

step 1000 :mobile error= 0.3365797 step 1000 :sensor error= 0.6412415 step 1000 :total error= 0.9778478

References.

Wu, X., Guo, J., Xian, K., Zhou, X., 2018. Hierarchical travel demand estimation using multiple data sources: A forward and backward propagation algorithmic framework on a layered computational graph. Transportation Research Part C: Emerging Technologies 96, 321-346.