

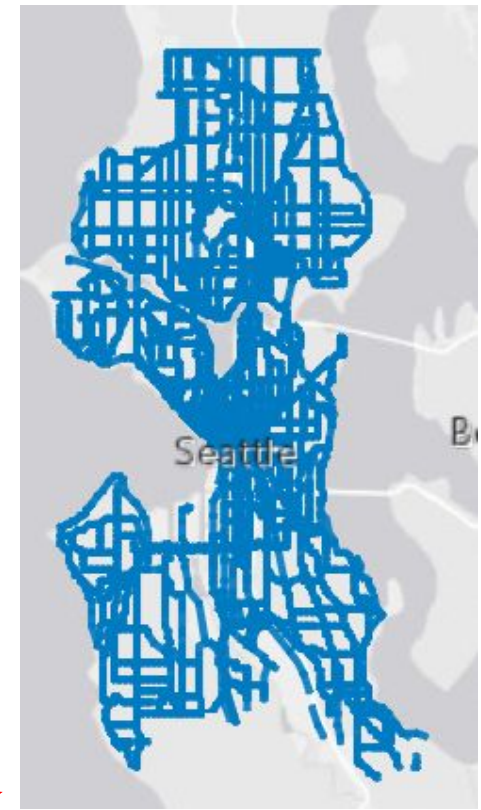


Final Presentation

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Problems

- Transportation accounts for 60% of total core emissions in Seattle, 61% percent of which is attributed to gasoline/diesel sources
- Population increased 25% from 2008 - 2018, projected to continue and intensify city-wide traffic burden
- Citizen survey data indicates current transportation must be more robust and equitable, especially for BIPOC communities
- Large data sets make it difficult to visualize

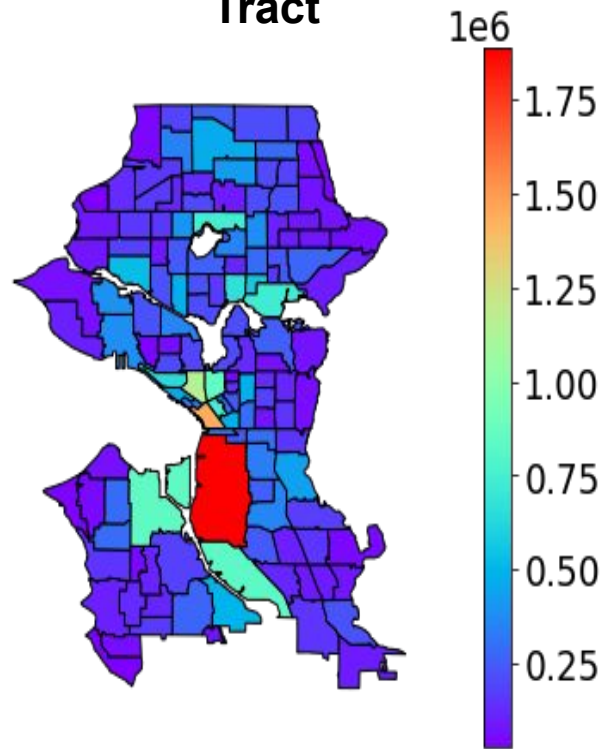


From Seattle.gov: 2018 Traffic Flow Counts

Background and Scope

- Modeling the impact on traffic can give an idea of which features most affect flow
- Visualizing these changes regionally allow for a regional approach to discover the best solutions for specific areas of Seattle
- **Questions:**
 - How can we use data science to predict traffic volumes based on urban features?
 - How can data from traffic flow be effectively visualized?

2015 City of Seattle
Traffic Data by Census
Tract



Chloropleth Plot
Generated in geoplot

Technology Overview: Geographic Information Systems

Objective: Use python to create interactive plots to visualize traffic and input feature data over geographic areas



GeoPandas

Most useful packages:

ArcGIS

Geopandas: geographical data can be stored in Pandas-like dataframes. Geographies are represented in terms of Shapely shapes - points, linestrings, polygons, etc. Shapely spatial functions can then be performed while maintaining the link to the data

Shapely: allows us to merge data based on geographic location - i.e. point in polygon, line intersecting polygon, etc.

Folium: Creates visually pleasing, interactive, detailed maps of geospatial data

Data Processing Workflow

1



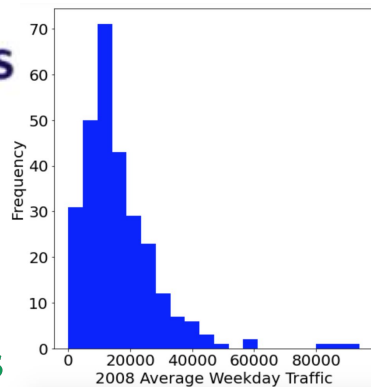
2008_Traffic_Flow_Counts									
OBJECTID	GEOBASID	DOWNTOWN	COMPKEY	STNAME	OID	NAME	YEAR	SECKEY	AAWDOT
1	94050370	N	12522	RENTON AVE S	196	RENTON AVE S, N/O S CLOVERDALE ST	2008	12522	8700
2	95000050	N	8762	ASHPORT WAY S	152	ASHPORT WAY S, N/O S NORFOLK ST	2008	8762	12750
3	127100040	N	16114	N NORTHGATE WAY	31	N NORTHGATE WAY, NW/O ASH/NORTH AVE N	2008	16114	26700
4	123400090	N	15794	N 60TH ST	166	N 60TH ST, NW/O LINDORA AVE N	2008	15794	8800
5	95000200	Y	2762	2ND AVE	80	2ND AVE, NW/O LINDORA ST	2008	2762	11900
6	80150420	N	11190	LAKE CITY WAY NE	161	LAKE CITY WAY NE, S/O NE 145TH ST	2008	11190	30300
7	78800080	Y	11055	JAMES ST	63	JAMES ST, NE/O 7TH AVE	2008	11055	31900
8	71050070	N	10795	GREENWOOD AVE N	96	GREENWOOD AVE N, S/O N 145TH ST	2008	10795	22900
9	94050400	N	12525	RENTON AVE S	197	RENTON AVE S, SE/O S HENDERSON ST	2008	12525	7200
10	31300190	Y	6138	4TH AVE	54	4TH AVE, NW/O LINDORA ST	2008	6138	13600
11	63200340	N	9992	DELRIDGE WAY SW	125	DELRIDGE WAY SW, NW/O SW CAMBRIDGE ST	2008	9992	13600
12	300310	N	1221	1ST AVE S	87	1ST AVE S, S/O S LUCKLE ST	2008	1221	17400
13	11800110	N	15163	N 120TH ST	192	N 120TH ST, NW/O ASH/NORTH AVE N	2008	15163	19400
14	26200150	N	5324	34TH AVE W	91	34TH AVE W, N/O W BARNETT ST	2008	5324	5100
15	13270250	N	17051	NE 56TH ST	135	NE 56TH ST, E/O 26TH AVE NE	2008	17051	5700
16	20800400	N	4471	3RD AVE NW	245	3RD AVE NW, S/O NW 80TH ST	2008	4471	8700
17	21500020	N	4641	30TH AVE NE	244	30TH AVE NE, S/O NE 145TH ST	2008	4641	6300

Datasets from
public records



GeoPandas

2



Traffic Flow
Distributions

3

ML
(DNN)

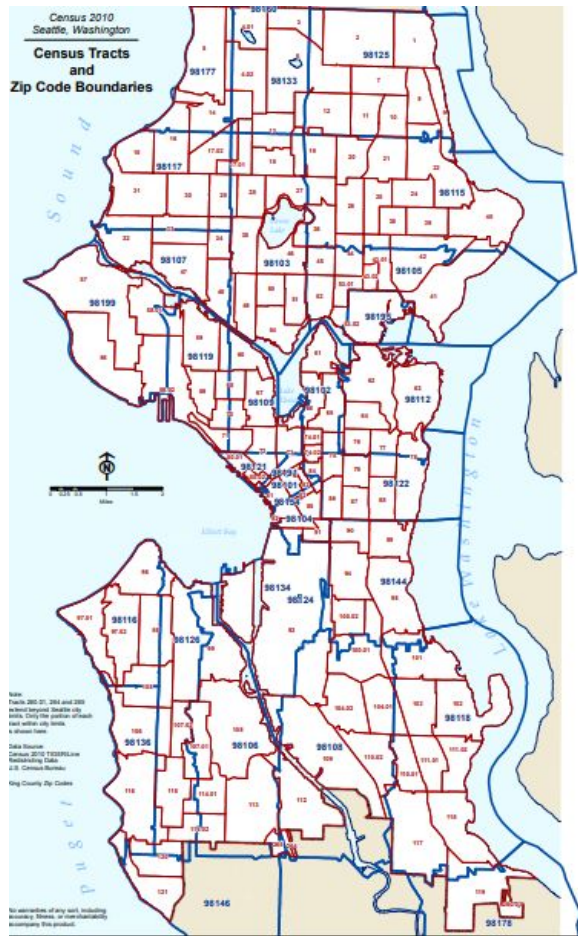
4

Final
Visualization

Key Questions:

- What geographic level should we be looking at for our dataset?
- How can we deal with different reporting between different datasets?

Zip Codes as a Geographic Marker



-Looking at every individual street could obscure area-level trends, the same is true for a city-wide view

-Here several census tracts are contained within zip codes, we can sum up these data to get a representative intermediate-level pictures

-This can be accomplished through Shapely sjoin Feature, which can group the data sets into larger pre-defined features

Data Cleaning: A geographic approach

Objective: Use spatial aspects of geographical data to organize input feature data into geographic locations

Zip



Data Cleaning: A geographic approach

Objective: Use spatial aspects of geographical data to organize input feature data into geographic locations

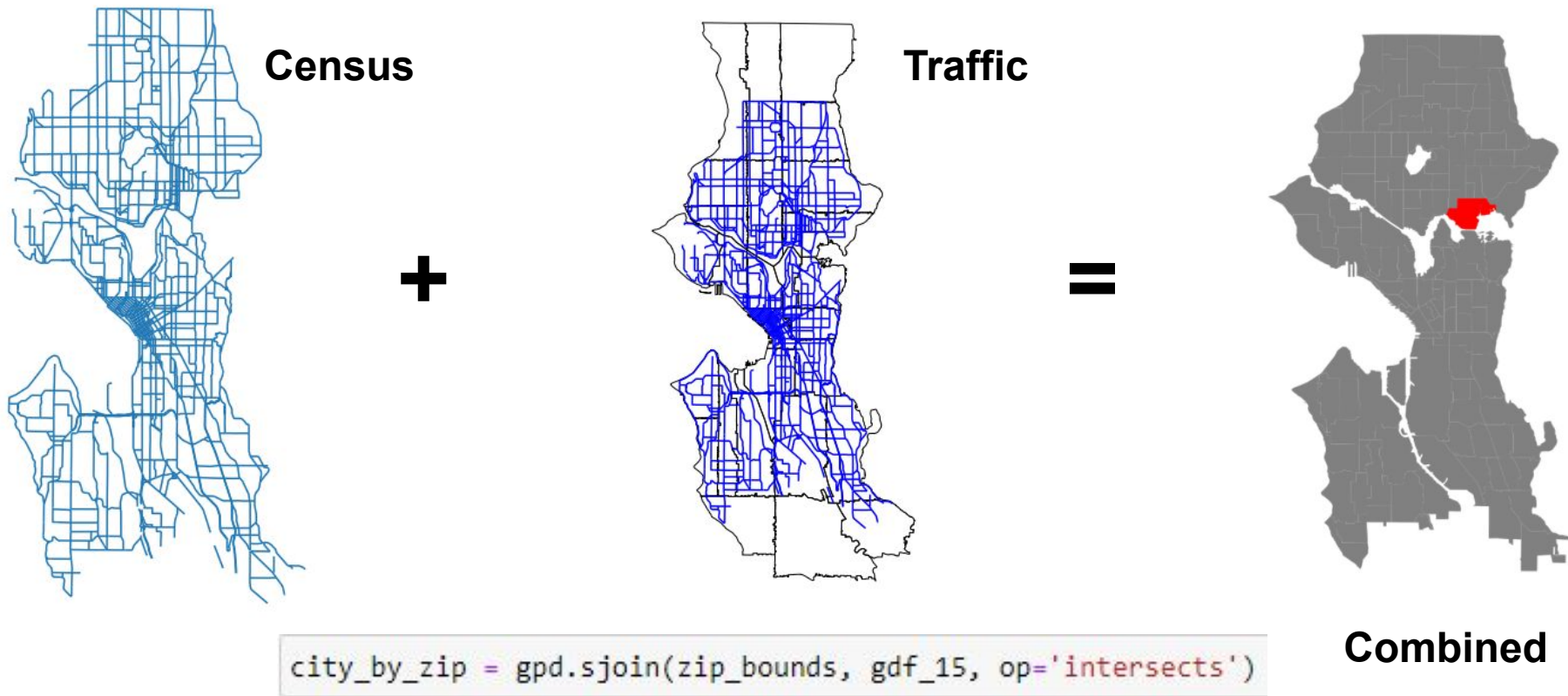
Traffic



```
city_by_zip = gpd.sjoin(zip_bounds, gdf_15, op='intersects')
```

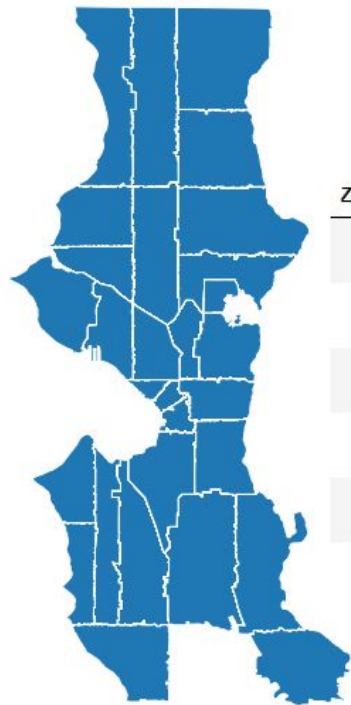

Data Cleaning: A geographic approach

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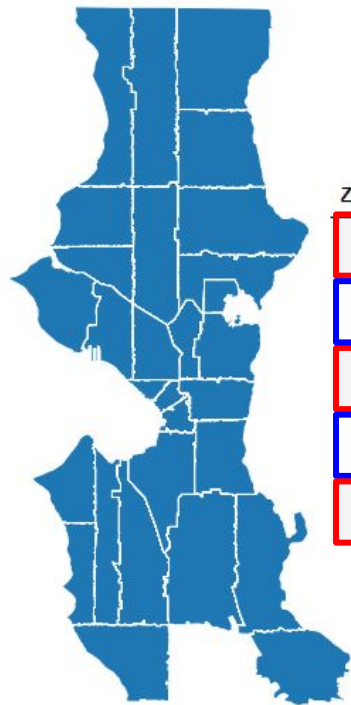
Objective: Use spatial aspects of geographical data to organize input feature data into geographic locations



ZIPCODE		geometry	NAME10	SHAPE_Area_left	index_right	YEAR	AAWDT	GEOBASID	STNAME	SHAPE_Length
98101		POLYGON ((-122.34598 47.60892, -122.34490 47.6...	74.02	1.470012e+07	1163	2015	10639.335836	800.0	ALASKAN WAY	1245.144941
98121		POLYGON ((-122.36110 47.61854, -122.36095 47.6...	81.00	1.225219e+07	1163	2015	10639.335836	800.0	ALASKAN WAY	1245.144941
98101		POLYGON ((-122.34598 47.60892, -122.34490 47.6...	74.02	1.470012e+07	1186	2015	2500.000000	823.0	VIRGINIA ST	372.729354
98121		POLYGON ((-122.36110 47.61854, -122.36095 47.6...	81.00	1.225219e+07	1186	2015	2500.000000	823.0	VIRGINIA ST	372.729354
98101		POLYGON ((-122.34598 47.60892, -122.34490 47.6...	74.02	1.470012e+07	1197	2015	11000.000000	705.0	ALASKAN WAY	613.438180

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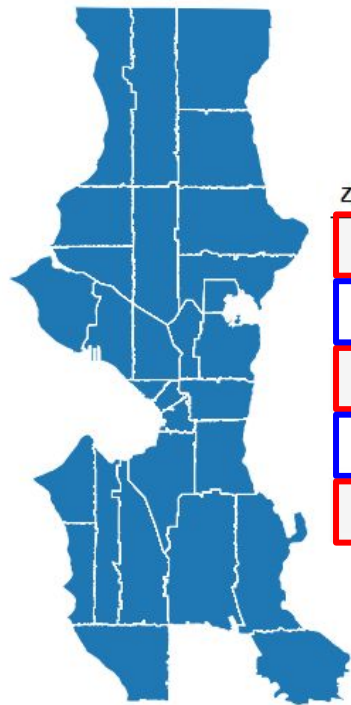
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98101	POLYGON ((-122.34598 47.60892, -122.34490 47.6...	74.02	1.470012e+07	1186	2015	2500.000000	823.0	VIRGINIA ST	372.729354
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98101	POLYGON ((-122.34598 47.60892, -122.34490 47.6...	74.02	1.470012e+07	1197	2015	11000.000000	705.0	ALASKAN WAY	613.438180

```
traffic_zones = city_by_zip.dissolve(by='ZIPCODE', aggfunc = sum)
```

Data Cleaning: A geographic approach

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	NAME10		geometry	AAWDT
ZIPCODE				
98101	13323.60	POLYGON	((-122.34598 47.60892, -122.34490 47.6...	1.877668e+06
98102	2738.74	POLYGON	((-122.33574 47.64203, -122.33108 47.6...	4.782904e+05
98103	5670.00	POLYGON	((-122.35808 47.69966, -122.35741 47.6...	1.880369e+06
98104	13944.00	POLYGON	((-122.34105 47.59627, -122.34031 47.5...	1.847450e+06
98105	6560.00	MULTIPOLYGON	(((-122.32859 47.66646, -122.3285...	1.762661e+06

```
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```

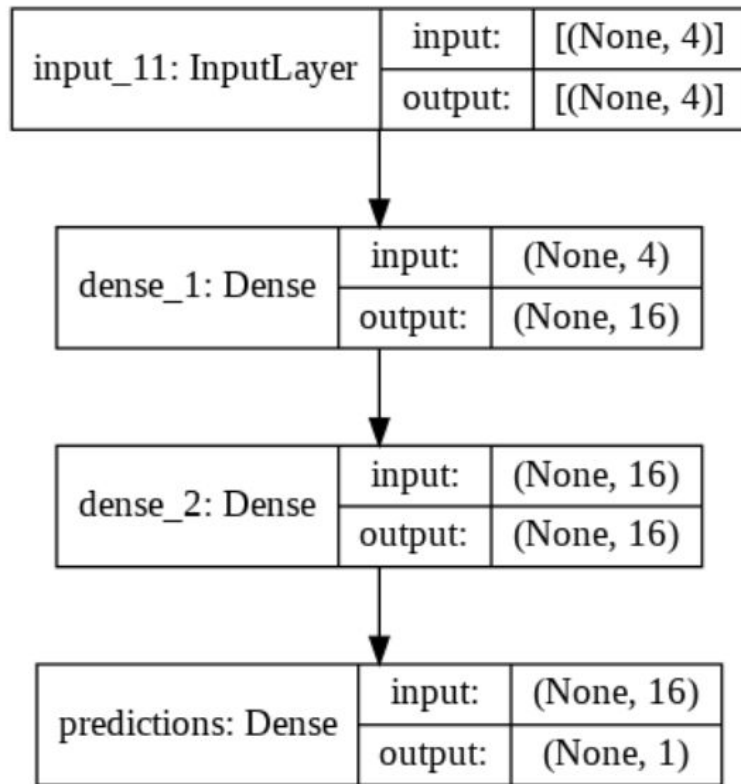

Demo: Interactive plots using folium

http://localhost:8888/view/map_html/choropleth_map_v3.html

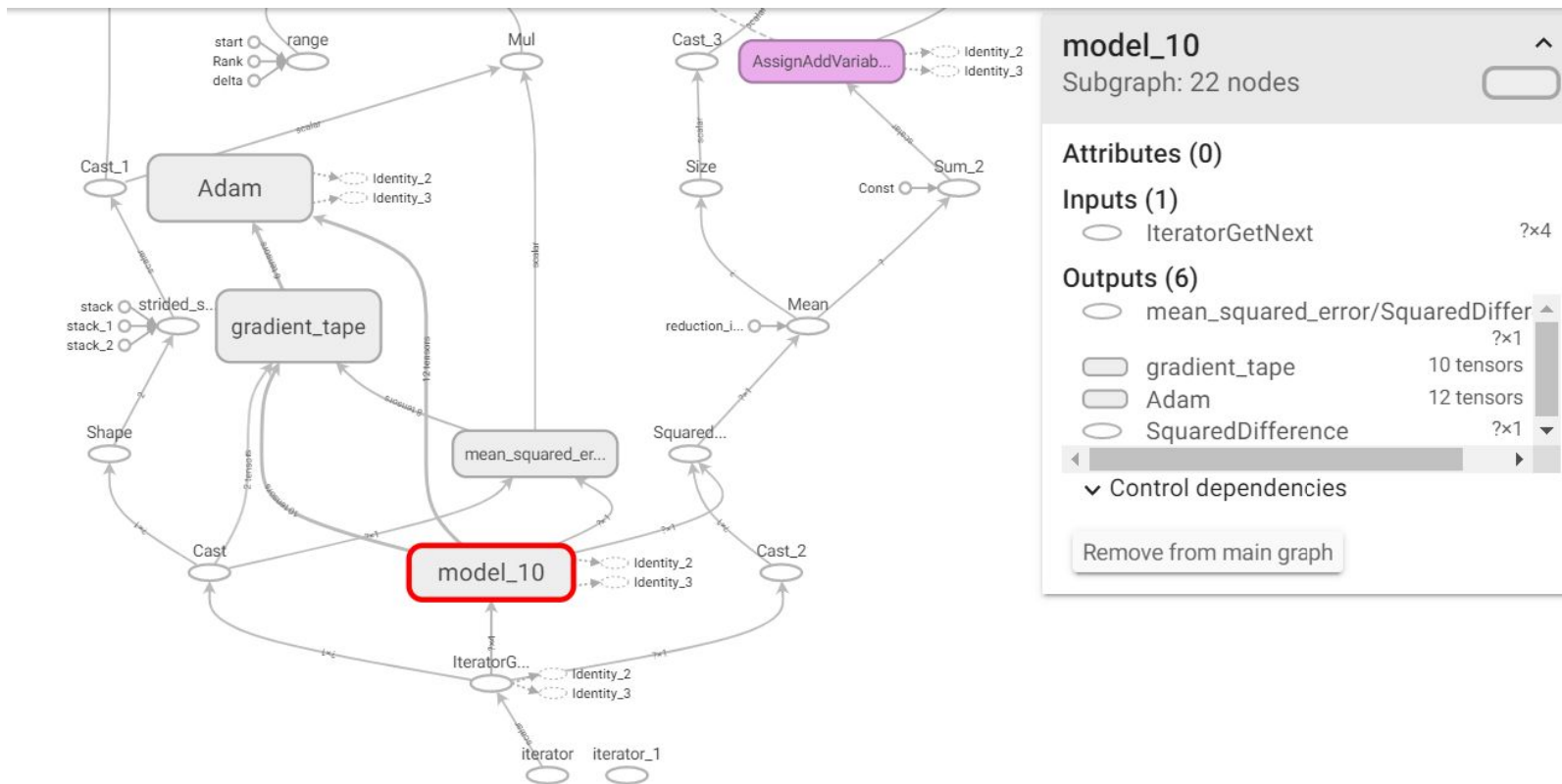


Visualize the model

- Make use of the 'keras.utils.plot_model' function in Tensorflow
- The structure is of two dense layer, each has 16 neurons, with tanh activation



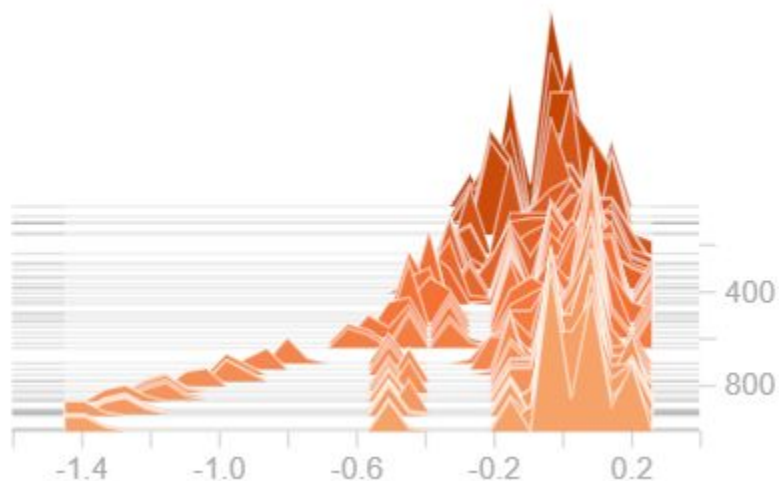
Visualize the Neural Network



Visualize the Weight through epochs

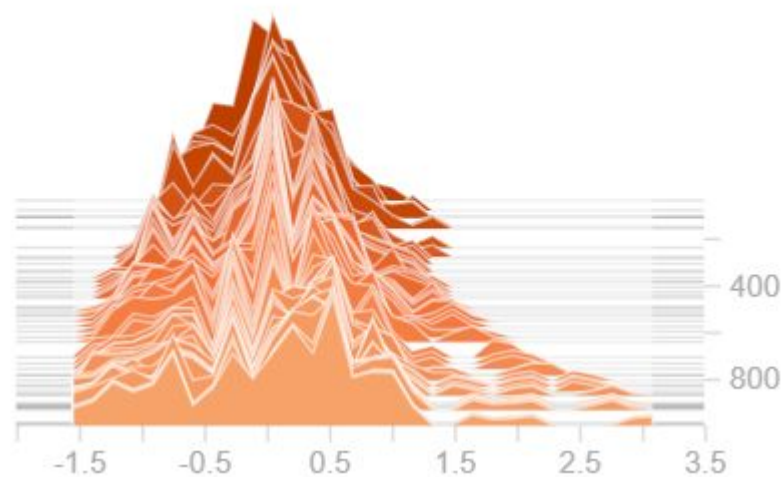
dense_1/bias_0

20210316-062553/train

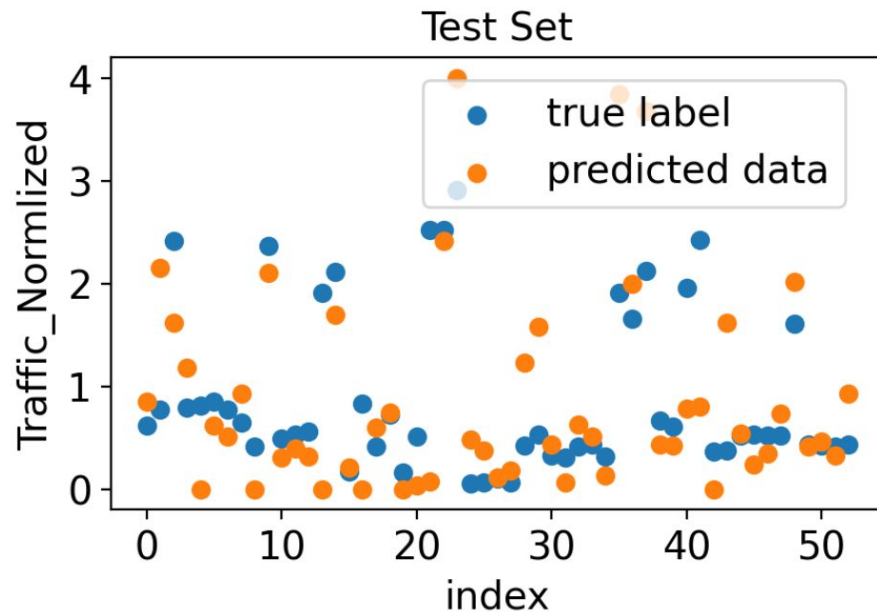
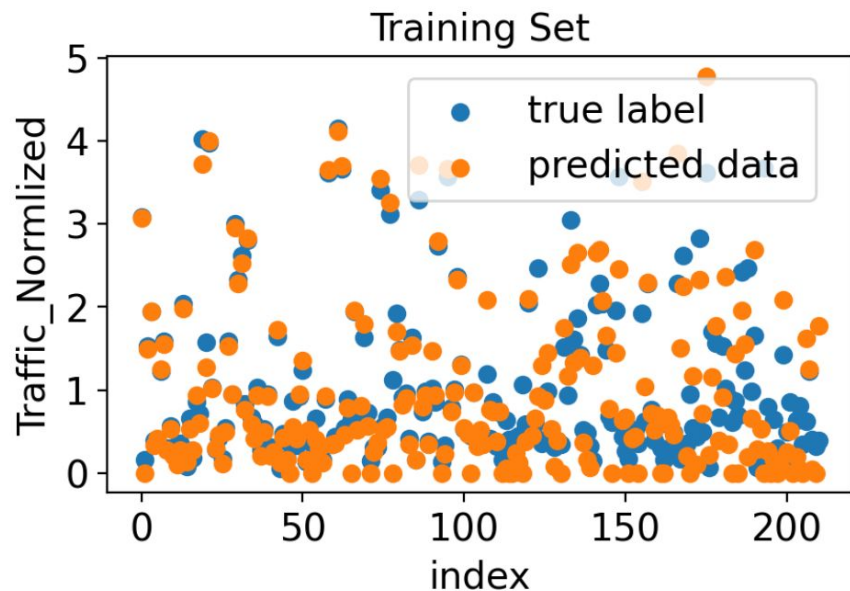


dense_1/kernel_0

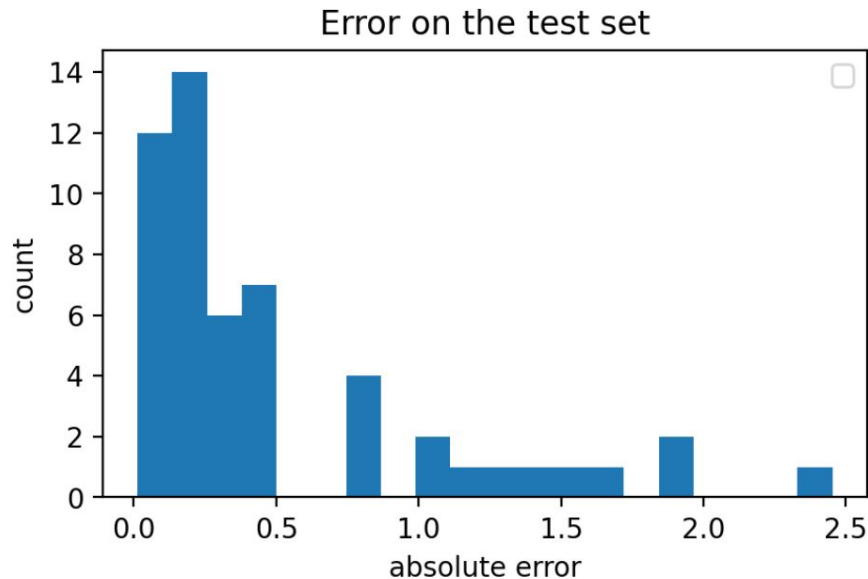
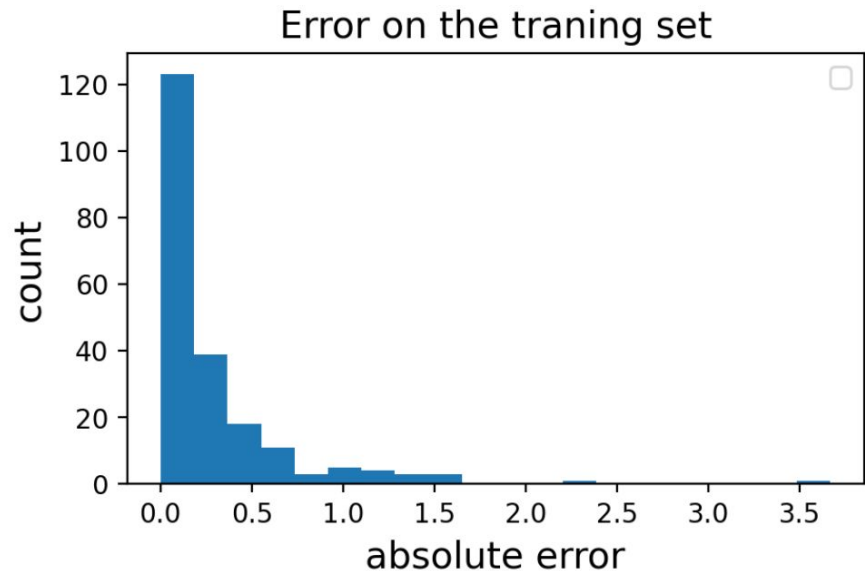
20210316-062553/train



Compare the true label with the predicted label



Compare the error on the training set and the test set



Loss verses epochs

