Trackintel case study

June 2, 2022

This notebook presents a case study to jointly analyse four different tracking datasets using Trackintel. Three of the datasets that are used in this case study can not be published to protect the privacy of the participants. You can find an executable example notebook for trackintel here: binder and code.

Imports

[305]:
```
import os, sys
from collections import defaultdict
import pickle
import datetime

import numpy as np
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import pytz
import json
import seaborn as sns
from shapely.geometry import Point, Polygon
from sqlalchemy import create_engine

from IPython.display import Image
from IPython.core.display import HTML

import trackintel as ti
from trackintel.analysis.tracking_quality import temporal_tracking_quality
from trackintel.analysis.modal_split import calculate_modal_split
from trackintel.visualization.modal_split import plot_modal_split
from trackintel.analysis.labelling import predict_transport_mode
plt.rcParams.update({"font.size": 15})
```

Define paths & PostGIS connection

[42]:
```
# output directory to save all outputs
out_path = "temp"
os.makedirs(out_path, exist_ok=True)
```

```
# Geolife data
path_to_geolife = "Geolife Trajectories 1.3/Data"

# for postgis
DBLOGIN_FILE_GC = "../../dblogin_commit.json"
DBLOGIN_FILE_yumuv = "../../dblogin_mielab.json"

with open(DBLOGIN_FILE_GC) as json_file:
    LOGIN_DATA_GC = json.load(json_file)

with open(DBLOGIN_FILE_yumuv) as json_file:
    LOGIN_DATA_YUMUV = json.load(json_file)

engine_gc = create_engine(
    "postgresql://{user}:{password}@{host}:{port}/{database}".format(
        **LOGIN_DATA_GC
    )
)
engine_yumuv = create_engine(
    "postgresql://{user}:{password}@{host}:{port}/{database}".format(
        **LOGIN_DATA_YUMUV
    )
)
engine_casestudy = create_engine(
    "postgresql://{user}:{password}@{host}:{port}/case_study_cache".format(
        **LOGIN_DATA_YUMUV
    )
)

CRS_WGS84 = "epsg:4326"
```

[30]:
```
# short names of the four included datasets
studies = ["gc1", "gc2", "yumuv_graph_rep", "geolife"]

# Full names for plotting
study_mapping = {
    "gc1": "Green Class 1",
    "gc2": "Green Class 2",
    "yumuv_graph_rep": "Yumuv",
    "geolife": "Geolife",
}
```

1 Dataset loading and preprocessing

1.1 Datasets

We include the data from four tracking studies with two different tracking data types.

1.1.1 Green Class 1 & 2

The Green Class 1 & 2 studies were conducted in collaboration with the Swiss Federal Railway Systems (SBB) under the project name SBB Green Class In both studies, participants were given full access to all public transport in Switzerland. In addition, the participants from the first Green Class study (Green Class 1) received an electric vehicle and the ones from the second study (Green Class 2) an e-bike. Study participants were tracked with a GNSS-based application (app) that provides partially preprocessed data as staypoints and triplegs.

1.1.2 Geolife

The open-source Geolife dataset covers the movement of employees of Microsoft Research Asia. The dataset is from around 2012 and was still recorded with dedicated GPS-only trackers. As the study took place in an urban area the GPS was unreliable and there are many gaps in the dataset. However, Geolife is still one of the few publicly available tracking datasets.

1.1.3 Yumuv

The yumuv study investigated the impact of a Mobility-as-a-Service app that integrates shared e-scooters, e-bikes and public transport. In the yumuv study, participants were divided into control and treatment group and were tracked for three months using an app that already provides staypoints and triplegs.

1.1.4 Data import and preprocessing

One main advantage of trackintel is its ability to standardize the preprocessing of tracking data. For this, the different datasets have to be imported to geopandas dataframes that fulfill the requirements described on `https://trackintel.readthedocs.io/en/latest/modules/model.html`.

The trackintel data model consists of these different classes:

- positionfixes [pfs]: Raw GPS data.
- staypoints [sp]: Locations where a user spent a minimal time.
- triplegs [tpls]: Segments covered with one mode of transport.
- locations [loc]: Clustered staypoints.
- trips: Segments between consecutive activity staypoints (special staypoints that are not just waiting points).
- tours: Sequences of trips which start and end at the same location (if the column 'journey' is True, this location is home).

The Geolife dataset consists of only positionfixes while the other datasets are already processed to staypoints and triplegs by the tracking app. We will now import all datasets and combine them on the staypoints / triplegs level.

1.2 Import Geolife

Geolife is an important benchmark dataset. Trackintel therefore offers a dedicated function that reads in the Geolife dataset. The import function takes care of the required column format and names.

[24]:
```
import trackintel
from trackintel.io.dataset_reader import read_geolife

pfs_geolife, _ = read_geolife(path_to_geolife, print_progress=True)
pfs_geolife[["user_id", "tracked_at", "geom", "elevation"]].head(3)
```

```
100%
182/182 [01:18<00:00,  2.32it/s]
```

[24]:

id	user_id	tracked_at	geom	elevation
7634985	0	2008-10-23 02:53:04+00:00	POINT (116.31842 39.98470)	149.9616
7634986	0	2008-10-23 02:53:10+00:00	POINT (116.31845 39.98468)	149.9616
7634987	0	2008-10-23 02:53:15+00:00	POINT (116.31842 39.98469)	149.9616

1.2.1 Geolife - Generate staypoints

We generate staypoints from the positionfixes and define all staypoints as relevant activities if they are longer than 25 minutes.

[26]:
```
# extract staypoints
pfs_geolife, sp_geolife = pfs_geolife.as_positionfixes.generate_staypoints(
    gap_threshold=24 * 60,
    include_last=True,
    print_progress=True,
    dist_threshold=200,
    time_threshold=30,
    n_jobs=4,
)
sp_geolife["study"] = "Geolife"

# add activity flag to staypoints
sp_geolife = sp_geolife.as_staypoints.create_activity_flag(
    method="time_threshold", time_threshold=25
)
sp_geolife.head(3)
```

```
100%|
182/182 [02:30<00:00,  1.21it/s]
```

[26]:

id	user_id	started_at	finished_at	elevation	geom	study	is_activity
0	0	2008-10-23 03:03:45+00:00	2008-10-23 04:08:07+00:00	61.7220	POINT (116.29917 39.98341)	Geolife	True
1	0	2008-10-23 04:32:52+00:00	2008-10-23 09:42:25+00:00	53.9496	POINT (116.32451 39.99967)	Geolife	True
2	0	2008-10-23 11:10:42+00:00	2008-10-24 02:10:09+00:00	26.8224	POINT (116.32105 40.00917)	Geolife	True

1.2.2 Geolife - Generate triplegs

[27]:
```
%%time
pfs_geolife, tpls_geolife = pfs_geolife.as_positionfixes.generate_triplegs(
    sp_geolife, method="between_staypoints", gap_threshold=25
)
tpls_geolife["study"] = "Geolife"
tpls_geolife.head(3)
```

```
CPU times: user 6min 20s, sys: 38.7 s, total: 6min 58s
Wall time: 7min 31s
```

[27]:

id	user_id	started_at	finished_at	geom	study
0	0	2008-10-23 02:53:04+00:00	2008-10-23 03:03:40+00:00	LINESTRING (116.31842 39.98470, 116.31845 39.9...	Geolife
1	0	2008-10-23 04:08:07+00:00	2008-10-23 04:32:47+00:00	LINESTRING (116.28680 39.99578, 116.28545 39.9...	Geolife
2	0	2008-10-23 09:42:25+00:00	2008-10-23 11:10:37+00:00	LINESTRING (116.32016 40.00478, 116.32039 40.0...	Geolife

1.3 Import Green Class 1 & 2

The green class datasets are stored in a postgis database and were already preprocessed to staypoints (static behavior) and triplegs (movement). To use them with trackintel, the data has to be adjusted to the data model. This means to create a geodataframe with the correct column names and timezone aware timestamps.

1.3.1 Green class - Staypoints

[35]:
```
sp_gc = []
for study in ["gc1", "gc2"]:
    # download data
    sp_temp = gpd.GeoDataFrame.from_postgis(
        sql=f"""SELECT id, user_id, started_at, finished_at, geometry_raw,\
            purpose_validated FROM {study}.staypoints\
            where started_at <= finished_at""",
        con=engine_gc,
        geom_col="geometry_raw",
        index_col="id",
    )

    # transform to trackintel dataframe
    sp_temp = ti.io.read_staypoints_gpd(
        sp_temp,
        geom_col="geom",
        tz="UTC",
        crs=CRS_WGS84,
        mapper={"geometry_raw": "geom", "purpose_validated": "purpose"},
    )

    # green class specific definition of activities
```

```
    sp_temp = sp_temp.as_staypoints.create_activity_flag(
        method="time_threshold", time_threshold=25
    )
    meaningful_purpose = ~sp_temp["purpose"].isin(["wait", "unknown"])
    sp_temp.loc[meaningful_purpose, "is_activity"] = True

    # keep study as attribute
    sp_temp["study"] = study_mapping[study]

    sp_gc.append(sp_temp)

# display output
print("Staypoints loaded successfully for GC1 and GC2.\
    Geometry not shown due to data protection.")
sp_temp.drop("geom", axis=1).head(3)
```

```
Staypoints loaded successfully for GC1 and GC2.    Geometry not shown due to
data protection.
```

[35]:

id	user_id	started_at	finished_at	purpose	is_activity	study
3644805	2379ddac-f662-49a5-84be-6fae5c91a7e3	2017-09-17 12:57:18.869999+00:00	2017-09-17 15:55:03.536000+00:00	leisure	True	Green Class 2
3680485	2379ddac-f662-49a5-84be-6fae5c91a7e3	2017-09-28 14:41:47.967000+00:00	2017-09-28 16:11:56.680000+00:00	errand	True	Green Class 2
3680768	2379ddac-f662-49a5-84be-6fae5c91a7e3	2017-09-28 16:22:26.680000+00:00	2017-09-28 16:32:23.947999+00:00	unknown	False	Green Class 2

1.3.2 Green class - Triplegs

[36]:
```
tpls_gc = []
for study in ["gc1", "gc2"]:
    # downlaod data using geopandas
    tpls_temp = gpd.GeoDataFrame.from_postgis(
        sql=f"""SELECT id, user_id, started_at, finished_at, mode_validated
            as mode, mode_validated as mode_detailed,
            geometry FROM {study}.triplegs where ST_isValid(geometry)""",
        con=engine_gc,
        crs=CRS_WGS84,
        geom_col="geometry",
        index_col="id",
    )
    # transform to trackintel dataframe
    tpls_temp = ti.io.read_triplegs_gpd(
        tpls_temp,
        geom_col="geom",
        crs=CRS_WGS84,
        tz="UTC",
        mapper={"geometry": "geom"},
    )
    # keep study as attribute
    tpls_temp["study"] = study_mapping[study]
```

```
    tpls_gc.append(tpls_temp)

# display output
print("Triplegs loaded successfully for GC1 and GC2.\
    Geometry not shown due to data protection.")
tpls_temp.drop("geom", axis=1).head(3)
```

```
Triplegs loaded successfully for GC1 and GC2.    Geometry not shown due to data
protection.
```

[36]:

id	user_id	started_at	finished_at	mode	mode_detailed	study
4350776	c9aa08e2-1a5d-4d41-ae62-6110a9072b23	2018-05-21 11:52:32.192009+00:00	2018-05-21 11:57:26+00:00	Mode::Ecar	Mode::Ecar	Green Class 2
4350859	c9aa08e2-1a5d-4d41-ae62-6110a9072b23	2018-05-22 06:38:32+00:00	2018-05-22 06:41:18+00:00	Mode::Walk	Mode::Walk	Green Class 2
3665724	75e13408-67ba-4c45-84ee-27b65de10680	2017-09-23 10:47:45.506017+00:00	2017-09-23 10:50:15.506000+00:00	Mode::Walk	Mode::Walk	Green Class 2

1.4 Import yumuv

The yumuv data is stored in a postgis database and it is already available as staypoints and triplegs. To use them with trackintel, the data has to be adjusted to the data model. This means to create a geodataframe with the correct column names and timezone aware timestamps. We furthermore conduct two additional preprocessing steps:

- We filter the tracking duration to the duration of the study which took place for most users from the 13th of July 2020 to the 15th of November 2020.
- We offset the user ids by a constant to be able to combine the data later with the other datasets without overlaps.

1.4.1 yumuv - Staypoints

[37]:
```
min_date = datetime.datetime(year=2020, month=7, day=13, tzinfo=pytz.utc)
max_date = datetime.datetime(year=2020, month=11, day=15, tzinfo=pytz.utc)
```

[43]:
```
sp_yumuv = ti.io.read_staypoints_postgis(
    "select id, user_fk, started_at, finished_at,\
    geometry from yumuv.staypoint",
    con=engine_yumuv,
    geom_col="geometry",
    crs=CRS_WGS84,
    index_col="id",
    tz="UTC",
    mapper={"user_fk": "user_id"},
)
sp_yumuv = sp_yumuv.rename({"geometry": "geom"}, axis=1).set_geometry("geom")

sp_yumuv["study"] = "Yumuv"

# yumuv specific definition of activities
sp_yumuv = sp_yumuv.as_staypoints.create_activity_flag(time_threshold=25)
```

```
# offset user id to avoid conflicts with other studies
sp_yumuv["user_id"] = sp_yumuv["user_id"] + 10000

# filter study duration
sp_date_flag = (sp_yumuv["started_at"] >= min_date) & (
    sp_yumuv["finished_at"] <= max_date)
sp_yumuv = sp_yumuv[sp_date_flag]

# display output
print("Staypoints loaded successfully for Yumuv.\
    Geometry not shown due to data protection.")
sp_yumuv.drop("geom", axis=1).head(3)
```

```
Staypoints loaded successfully for Yumuv.    Geometry not shown due to data
protection.
```

[43]:

id	user_id	started_at	finished_at	study	is_activity
6773023	15529	2020-08-28 17:32:47+00:00	2020-08-29 10:56:01+00:00	Yumuv	True
6678616	15285	2020-08-22 12:23:03+00:00	2020-08-22 13:40:37+00:00	Yumuv	True
6109237	15003	2020-07-13 12:20:46+00:00	2020-07-13 12:57:39+00:00	Yumuv	True

1.4.2 yumuv - Triplegs

[44]:
```
tpls_yumuv = ti.io.postgis.read_triplegs_postgis(
    """select distinct on (id) id, user_fk, started_at,
    finished_at, track_mode_corrected,
    geometry FROM yumuv.tripleg where ST_isvalid(geometry)""",
    con=engine_yumuv,
    geom_col="geometry",
    crs=CRS_WGS84,
    index_col="id",
    tz="UTC",
    mapper={"user_fk": "user_id"},
)
tpls_yumuv = tpls_yumuv.rename(
    {"geometry": "geom", "track_mode_corrected": "mode"}, axis=1
).set_geometry("geom")
tpls_yumuv["study"] = "Yumuv"

# offset user id
tpls_yumuv["user_id"] = tpls_yumuv["user_id"] + 10000

# filter study duration
tpls_date_flag = (tpls_yumuv["started_at"] >= min_date) & (
    tpls_yumuv["finished_at"] <= max_date
```

```
)
tpls_yumuv = tpls_yumuv[tpls_date_flag]

# display output
print("Triplegs loaded successfully for Yumuv.\
    Geometry not shown due to data protection.")
tpls_yumuv.drop("geom", axis=1).head(3)
```

```
Triplegs loaded successfully for Yumuv.    Geometry not shown due to data
protection.
```

[44]:

id	user_id	started_at	finished_at	mode	study
6097696	15018	2020-07-13 01:08:33+00:00	2020-07-13 01:11:53+00:00	walk	Yumuv
6097774	14982	2020-07-13 03:42:00+00:00	2020-07-13 03:44:21+00:00	walk	Yumuv
6097775	14982	2020-07-13 03:44:21+00:00	2020-07-13 03:49:35+00:00	train	Yumuv

1.5 Combine studies

All datasets are now loaded into the trackintel framework and all tracking data is represented as `staypoints` and `triplegs`. We can now represent all studies in a joint `staypoints` and a joint `triplegs` dataframe and process all studies jointly. To allow the joint analysis we have to perform the following steps:

- All staypoints and triplegs are combined in a single dataframe respectively.
- All user ids are represented as strings to have an id column with a single data type.
- We offset the ids of staypoints and triplegs so that they are unique across studies.

Furthermore we simplify the geometry of triplegs to reduce computation time.

1.5.1 All studies - combine staypoints

[45]:
```
staypoints = pd.concat([sp_geolife] + sp_gc + [sp_yumuv])
staypoints["user_id"] = staypoints["user_id"].astype(str)
```

1.5.2 All studies - combine triplegs

[46]:
```
triplegs = pd.concat([tpls_geolife] + tpls_gc + [tpls_yumuv])
triplegs["user_id"] = triplegs["user_id"].astype(str)
```

[47]:
```
triplegs["geom"] = triplegs.simplify(1e-5, preserve_topology=False)
```

1.5.3 Offset ids to ensure unique IDs

[49]:
```
for ix, study in enumerate(study_mapping.values()):
    sp_study_flag = staypoints["study"] == study
    tpls_study_flag = triplegs["study"] == study
```

```
    staypoints.loc[sp_study_flag].index = staypoints.loc[
            sp_study_flag].index + ix * 10e7
    triplegs.loc[tpls_study_flag].index = triplegs.loc[
            tpls_study_flag].index + ix * 10e7
```

[50]:
```
# show a staypoint for each study (without user_id and geometry due to privacy)
staypoints[[
    "started_at", "finished_at", "study", "is_activity", "purpose"
]].groupby("study").head(1)
```

[50]:

id	started_at	finished_at	study	is_activity	purpose
0	2008-10-23 03:03:45+00:00	2008-10-23 04:08:07+00:00	Geolife	True	None
3552473	2017-08-17 17:22:12+00:00	2017-08-17 18:04:00+00:00	Green Class 2	True	home
6309557	2020-07-28 11:23:02+00:00	2020-07-28 13:22:05+00:00	Yumuv	True	None
1321494	2016-11-23 07:27:13.687000+00:00	2016-11-23 07:51:43.687000+00:00	Green Class 1	True	work

Finally we create a table that matches user ids to studies

[51]:
```
user_study_matching = staypoints[["user_id", "study"]].drop_duplicates()
user_study_matching = user_study_matching.set_index("user_id")
```

1.6 Joint preprocessing - Trips, tours and locations

The representation of human mobility as `staypoints` and `triplegs` is often not enough for a detailed analysis. We now use trackintel to process `staypoints` and `triplegs` futher into `trips`, `tours` and `locations`.

1.6.1 Create trips

[52]:
```
staypoints, triplegs, trips = ti.preprocessing.triplegs.generate_trips(
    staypoints=staypoints, triplegs=triplegs,
    gap_threshold=15, add_geometry=True
)
```

[53]:
```
trips = trips.join(user_study_matching, on="user_id")
```

[60]:
```
trips.head(3)
```

[60]:

id	user_id	started_at	finished_at	geom	origin_staypoint_id	destination_staypoint_id	study	tour_id	duration_s
0	0	2008-10-23 02:53:04+00:00	2008-10-23 03:03:40+00:00	MULTIPOINT (116.31842 39.98470, 116.29917 39.9...	NaN	0.0	Geolife	NaN	0.176667
1	0	2008-10-23 04:08:07+00:00	2008-10-23 04:32:47+00:00	MULTIPOINT (116.29917 39.98341, 116.32451 39.9...	0.0	1.0	Geolife	NaN	0.411111
2	0	2008-10-23 09:42:25+00:00	2008-10-23 11:10:37+00:00	MULTIPOINT (116.32451 39.99967, 116.32105 40.0...	1.0	2.0	Geolife	NaN	1.470000

1.6.2 Create locations

[54]:
```
staypoints, locations = ti.preprocessing.generate_locations(
    staypoints,
    epsilon=30,
    num_samples=1,
```

```
    distance_metric="haversine",
    print_progress=True,
    n_jobs=4,
)
```

```
100%
1172/1172 [00:13<00:00, 89.58it/s]
```

[55]:
```
locations = locations.join(user_study_matching, on="user_id")
```

[59]:
```
locations.head(3)
```

[59]:

id	user_id	center	extent	study
0	0	POINT (116.29917 39.98341)	POLYGON ((116.29952 39.98341, 116.29952 39.983...	Geolife
1	0	POINT (116.32446 39.99988)	POLYGON ((116.32439 39.99965, 116.32419 39.999...	Geolife
2	0	POINT (116.32089 40.00921)	POLYGON ((116.32155 40.00895, 116.32022 40.009...	Geolife

1.6.3 Create tours

[60]:
```
trips, tours = ti.preprocessing.generate_tours(
    trips, staypoints=staypoints, print_progress=True
)
tours["started_at"] = pd.to_datetime(tours["started_at"])
tours["finished_at"] = pd.to_datetime(tours["finished_at"])
```

[57]:
```
tours = tours.join(user_study_matching, on="user_id")
```

[58]:
```
tours.head(3)
```

[58]:

id	user_id	started_at	finished_at	origin_staypoint_id	destination_staypoint_id	trips	location_id	study	nb_hops
0	0	2008-11-13 13:53:46+00:00	2008-11-14 01:59:25+00:00	19.0	21.0	[21, 22]	1	Geolife	2
1	0	2008-11-14 11:17:04+00:00	2008-11-14 11:18:34+00:00	25.0	26.0	[26]	2	Geolife	1
2	0	2008-11-14 07:03:48+00:00	2008-11-14 16:29:15+00:00	23.0	27.0	[24, 25, 26, 27]	11	Geolife	4

2 Dataset comparison

2.1 Simple Statistics

Number of users, number of trips, number of trips by user, etc

[61]:
```
overview_df = pd.DataFrame(index=study_mapping.values())

overview_df["nr_user"] = staypoints.groupby(by=["study"]).agg(
    {"user_id": "nunique"}
)
nr_user = overview_df["nr_user"]
```

```
# nb staypooints
overview_df["nr_sp"] = staypoints.groupby(by=["study"]).size()
overview_df["nr_staypoints_per_user"] = overview_df["nr_sp"] / nr_user

# nb triplegs
overview_df["nr_tpls"] = triplegs.groupby(by=["study"]).size()
overview_df["nr_triplegs_per_user"] = overview_df["nr_tpls"] / nr_user

# nb trips
overview_df["nr_trips"] = trips.groupby(by=["study"]).size()
overview_df["nr_trips_per_user"] = overview_df["nr_trips"] / nr_user
# nb locations

overview_df["nr_loc"] = locations.groupby(by=["study"]).size()
overview_df["nr_locations_per_user"] = overview_df["nr_loc"] / nr_user

# nb tours
overview_df["nr_tours"] = tours.groupby(by=["study"]).size()
overview_df["nr_tours_per_user"] = overview_df["nr_tours"] / nr_user
```

[62]:
```
overview_df
```

[62]:

	nr_user	nr_sp	nr_staypoints_per_user	nr_tpls	nr_triplegs_per_user	nr_trips	nr_trips_per_user
Green Class 1	139	326925	2351.978417	465189	3346.683453	241827	1739.762590
Green Class 2	50	87884	1757.680000	128618	2572.360000	61421	1228.420000
Yumuv	806	326271	404.802730	502292	623.191067	199735	247.810174

	nr_loc	nr_locations_per_user	nr_tours	nr_tours_per_user
Green Class 1	104497	751.776978	94977	683.287770
Green Class 2	35715	714.300000	22709	454.180000
Yumuv	127320	157.965261	83019	103.001241

2.2 Trip characteristics

- How many trips comprise one tour on average? How many triplegs comprise a trip?
- What is the average trip duration / distance?

2.2.1 Number of hops in tours

[63]:
```
tours["nb_hops"] = tours["trips"].apply(lambda x: len(x))
overview_df["avg_hops_tours"] = tours.groupby("study")["nb_hops"].mean()
```

[64]:
```
overview_df["avg_hops_tours"]
```

[64]:
```
Green Class 1    2.725197
Green Class 2    2.656656
Yumuv            2.112806
Geolife          2.373469
Name: avg_hops_tours, dtype: float64
```

2.2.2 Trip duration

[65]:
```
trips["duration_s"] = (
    trips["finished_at"] - trips["started_at"]
    ).dt.total_seconds() / 3600
```

[66]:
```
overview_df[["mean_trip_dur", "std_trip_dur"]] = trips.groupby(
    "study"
)["duration_s"].aggregate(["mean", "std"])
```

[67]:
```
overview_df[["mean_trip_dur", "std_trip_dur"]]
```

[67]:

	mean_trip_dur	std_trip_dur
Green Class 1	0.522175	0.731360
Green Class 2	0.513715	0.753746
Yumuv	0.681057	0.911373
Geolife	0.640133	0.935874

2.2.3 Overall tracking period

[68]:
```
min_max_times_by_user = trips.groupby(["study", "user_id"]).aggregate(
    {"started_at": "min", "finished_at": "max"}
)
duration_by_user = (
    min_max_times_by_user[
        "finished_at"
    ] - min_max_times_by_user["started_at"]
).dt.total_seconds() / (3600 * 24)

overview_df[
    ["mean_tracking_period", "std_tracking_period"]
] = duration_by_user.groupby("study").aggregate(["mean", "std"])
```

[69]:
```
overview_df[["mean_tracking_period", "std_tracking_period"]]
```

[69]:

	mean_tracking_period	std_tracking_period
Green Class 1	401.639038	59.289224
Green Class 2	314.203054	76.458555
Yumuv	87.393827	38.954972
Geolife	193.216082	443.133363

2.2.4 Number of trips per day per user

[70]:
```
# average trips per day over full tracking period
nr_trips_per_user_per_day = (trips.groupby(
    ["study", "user_id"]
).size() / duration_by_user).groupby("study").mean()
overview_df["nr_trips_per_user_per_day"] = nr_trips_per_user_per_day
```

[71]:
```
overview_df["nr_trips_per_user_per_day"]
```

[71]:
```
Green Class 1    4.319424
Green Class 2    3.797688
Yumuv            3.131575
Geolife          1.701115
Name: nr_trips_per_user_per_day, dtype: float64
```

2.2.5 Trip distance

[72]:
```
# compute length
triplegs["length_in_m"] = ti.geogr.distances.calculate_haversine_length(
    triplegs
)
```

[73]:
```
# aggregate lengths
metrics_per_trip = triplegs.groupby(["study", "trip_id"]).agg(
    {"trip_id": "count", "length_in_m": "sum"}
)

# add to results
overview_df[
    ["nr_legs_per_trip", "avg_trip_length", "std_trip_length"]
] = metrics_per_trip.groupby("study").agg(
    {"trip_id": "mean", "length_in_m": ["mean", "std"]}
)
```

[74]:
```
overview_df[["nr_legs_per_trip", "avg_trip_length", "std_trip_length"]]
```

[74]:

	nr_legs_per_trip	avg_trip_length	std_trip_length
Green Class 1	1.923644	27353.308940	4.786795e+05
Green Class 2	2.094039	33656.574834	5.681591e+05
Yumuv	2.514616	16883.392910	1.004259e+05
Geolife	1.000000	36091.470622	3.163541e+06

2.2.6 Tracking quality (temporal coverage)

[75]:
```
triplegs_staypoints = pd.concat([triplegs, staypoints])
```

[76]:
```
tracking_quality_by_user_study = triplegs_staypoints.groupby(
    "study"
).apply(temporal_tracking_quality)
overview_df[
    ["mean_tracking_quality", "std_tracking_quality"]
] = tracking_quality_by_user_study.groupby("study")["quality"].agg(
    ["mean", "std"]
)
```

[77]:
```
overview_df[["mean_tracking_quality", "std_tracking_quality"]]
```

[77]:

	mean_tracking_quality	std_tracking_quality
Green Class 1	0.846193	0.170515
Green Class 2	0.753790	0.237544
Yumuv	0.766790	0.231347
Geolife	0.397451	0.317477

2.3 Finalize results in two tables

2.3.1 Present simple dataset statistics as nice table

[78]:
```
# basic info
overview_df.fillna(0, inplace=True)
df_basic = overview_df[
    [
        "nr_user",
        "mean_tracking_period",
        "std_tracking_period",
        "nr_loc",
        "nr_sp",
        "nr_tpls",
        "nr_trips",
        "nr_tours",
    ]
].astype(int)
```

[79]:
```
# format mean tracking period and its std nicely
df_basic["Tracking period (std)"] = df_basic.apply(
    lambda x: f"{x['mean_tracking_period']} ({x['std_tracking_period']})",
    axis=1
)
df_basic.drop(
    columns=["mean_tracking_period", "std_tracking_period"], inplace=True
)
```

[80]:
```
# set column values for data type and tracking technology
df_basic.loc[
    ["Green Class 1", "Green Class 2", "Yumuv"], "Input"
] = "Staypoints, Triplegs"
df_basic.loc["Geolife", "Input"] = "Positionfixes"

df_basic.loc[
    ["Green Class 1", "Green Class 2", "Yumuv"], "Study type"
] = "GNSS (app)"
df_basic.loc["Geolife", "Study type"] = "GPS tracker"
```

[81]:
```
# rename columns and index
df_basic = df_basic.rename(
    columns={
        "nr_user": "Users",
        "nr_loc": "Locations",
        "nr_sp": "Staypoints",
        "nr_tpls": "Triplegs",
        "nr_trips": "Trips",
        "nr_tours": "Tours",
    },
    index=study_mapping,
)
```

[82]:
```
# select the columns in the right order
df_basic = df_basic[
    [
        "Users",
        "Tracking period (std)",
        "Input",
        "Study type",
        "Locations",
        "Staypoints",
        "Triplegs",
        "Trips",
        "Tours",
    ]
]

df_basic
```

[82]:

	Users	Tracking period (std)	Input	Study type
Green Class 1	139	401 (59)	Staypoints, Triplegs	GNSS (app)
Green Class 2	50	314 (76)	Staypoints, Triplegs	GNSS (app)
Yumuv	806	87 (38)	Staypoints, Triplegs	GNSS (app)
Geolife	177	193 (443)	Positionfixes	GPS tracker

	Locations	Staypoints	Triplegs	Trips	Tours
Green Class 1	104497	326925	465189	241827	94977
Green Class 2	35715	87884	128618	61421	22709
Yumuv	127320	326271	502292	199735	83019
Geolife	13575	28877	30205	30199	7184

2.3.2 Present the trip statistics as nice table

[268]:
```
# Analysis table
df_detailed = overview_df[
    [
        "nr_trips_per_user_per_day",
        "mean_trip_dur",
        "std_trip_dur",
        "avg_hops_tours",
        "nr_legs_per_trip",
        "avg_trip_length",
        "std_trip_length",
        "mean_tracking_quality",
        "std_tracking_quality",
    ]
]

df_detailed = df_detailed.round(2)
```

[271]:
```
# # format mean and its std nicely in a single cell
to_km = lambda x: (x/1000).round(1)
df_detailed["Trip distance (std)"] = df_detailed.apply(
    lambda x: f"{to_km(x['avg_trip_length'])} ({to_km(x['std_trip_length'])})",
    axis=1
)
df_detailed["Trip duration (std)"] = df_detailed.apply(
    lambda x: f"{x['mean_trip_dur']} ({x['std_trip_dur']})", axis=1
)
df_detailed["Tracking quality (std)"] = df_detailed.apply(
    lambda x: f"{x['mean_tracking_quality']} ({x['std_tracking_quality']})",
    axis=1
)
```

[272]:
```
df_detailed = df_detailed.rename(
    columns={
        "nr_trips_per_user_per_day": "Trips per day",
        "avg_hops_tours": "Trips per tour",
        "nr_legs_per_trip": "Legs per trip",
    }
)
df_detailed.drop(
    [
        "avg_trip_length",
        "std_trip_length",
        "mean_tracking_quality",
        "std_tracking_quality",
        "mean_trip_dur",
```

```
        "std_trip_dur",
    ],
    axis=1,
    inplace=True,
)

df_detailed
```

[272]:

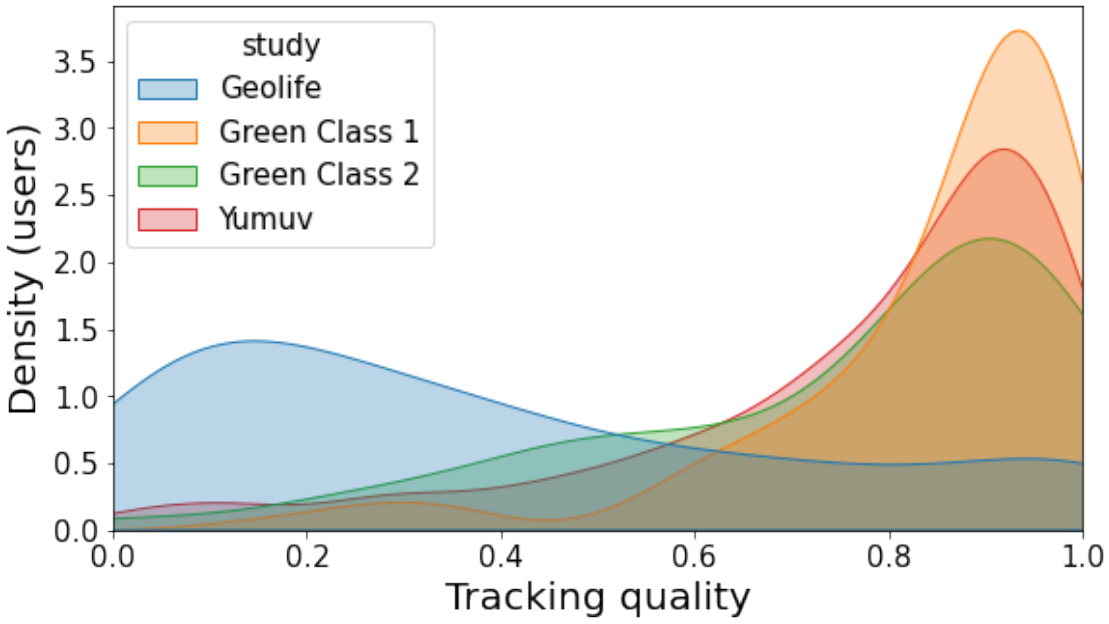
	Trips per day	Trips per tour	Legs per trip	Trip distance (std)	Trip duration (std)	Tracking quality (std)
Green Class 1	4.32	2.73	1.92	27.4 (478.7)	0.52 (0.73)	0.85 (0.17)
Green Class 2	3.80	2.66	2.09	33.7 (568.2)	0.51 (0.75)	0.75 (0.24)
Yumuv	3.13	2.11	2.51	16.9 (100.4)	0.68 (0.91)	0.77 (0.23)
Geolife	1.70	2.37	1.00	36.1 (3163.5)	0.64 (0.94)	0.4 (0.32)

2.4 KDE plot for user tracking quality distribution

We have calculated the temporal coverage of the tracking data as an indicator for the tracking quality. The indicator was calculted for every individual user. We'll now plot the distribution over users for each dataset.

[90]:
```
# pivot to match seaborn requirements
tracking_quality_df = tracking_quality_by_user_study.reset_index(
    level=0
).pivot(columns="study", values="quality")
```

[230]:
```
fig, ax = plt.subplots(figsize=(9, 5))
g = sns.kdeplot(
    data=tracking_quality_df,
    fill=True,
    alpha=0.3,
    legend=True,
    common_grid=True,
    common_norm=False,
    ax=ax,
)

plt.ylabel("Density (users)", fontsize=20)
plt.xlabel("Tracking quality", fontsize=20)
sns.move_legend(g, "upper left")
plt.xlim(0, 1)
plt.savefig(os.path.join(out_path, "tracking_quality_kde.pdf"))
plt.show()
```



2.5 Modal split dataset comparison

We'll now show how trackintel can be used to analyze the modal split and compare it between different studies using the trackintel function `calculate_modal_split`. The datasets GC1, GC2 & yumuv have mode labels available while geolife does not feature mode labels for all triplegs. We therefore use the trackintel function `predict_transport_mode` to create labels.

Another preprocessing step is required because all studies use different mode labels. All of them will be matched to the three categories `fast`, `motorized` and `slow`

[96]:
```
# Fill transport mode for geolife
is_geolife = triplegs["study"] == "Geolife"
triplegs.loc[is_geolife, "mode"] = predict_transport_mode(triplegs[is_geolife])
```

[97]:
```
# we need to map the mode labels from GC1, GC2 & Yumuv to the ones from geolife
mode_to_category = {
    "Mode::Airplane": "fast",
    "Mode::Train": "fast",
    "airplane": "fast",
    "fast_mobility": "fast",
    "fast": "fast",
    "car": "motorized",
    "Mode::Boat": "slow",
    "Mode::Bus": "motorized",
    "Mode::Car": "motorized",
    "Mode::Coach": "motorized",
    "Mode::Ecar": "motorized",
```

```
    "Mode::Tram": "motorized",
    "bus": "motorized",
    "coach": "motorized",
    "ecar": "motorized",
    "motorbike": "motorized",
    "tram": "motorized",
    "motorized_mobility": "motorized",
    "motorized": "motorized",
    "Mode::Bicycle": "slow",
    "Mode::Ebicycle": "slow",
    "Mode::Walk": "slow",
    "bicycle": "slow",
    "boat": "slow",
    "ebicycle": "slow",
    "kick_scooter": "slow",
    "ski": "slow",
    "train": "fast",
    "walk": "slow",
    "slow": "slow",
    "slow_mobility": "slow",
}

# change mode labels with the above mapping
triplegs["mode"] = triplegs["mode"].map(mode_to_category)
triplegs.dropna(subset=["mode"], inplace=True)
triplegs["mode"].unique()
```

[97]:
```
array(['slow', 'motorized', 'fast'], dtype=object)
```

2.5.1 Get modal split by count, duration and distance

[98]:
```
# count
modal_split_count = triplegs.groupby("study").apply(
    calculate_modal_split, metric="count", norm=True
)
modal_split_count = modal_split_count.droplevel(1)
modal_split_count
```

[98]:
```
mode                fast  motorized      slow
study
Geolife         0.009270   0.409317  0.581413
Green Class 1   0.128245   0.377709  0.494046
Green Class 2   0.138213   0.257223  0.604564
Yumuv           0.067272   0.259749  0.672979
```

[99]:
```
# duration
modal_split_duration = triplegs.groupby("study").apply(
```

```
    calculate_modal_split, metric="duration", norm=True
)
modal_split_duration = modal_split_duration.droplevel(1)
modal_split_duration
```

[99]:
```
mode               fast  motorized      slow
study
Geolife        0.025935   0.467538  0.506527
Green Class 1  0.281664   0.474181  0.244155
Green Class 2  0.285285   0.320476  0.394239
Yumuv          0.144173   0.358140  0.497688
```

[100]:
```
# distance
modal_split_distance = triplegs.groupby("study").apply(
    calculate_modal_split, metric="distance", norm=True
)
modal_split_distance = modal_split_distance.droplevel(1)
modal_split_distance
```

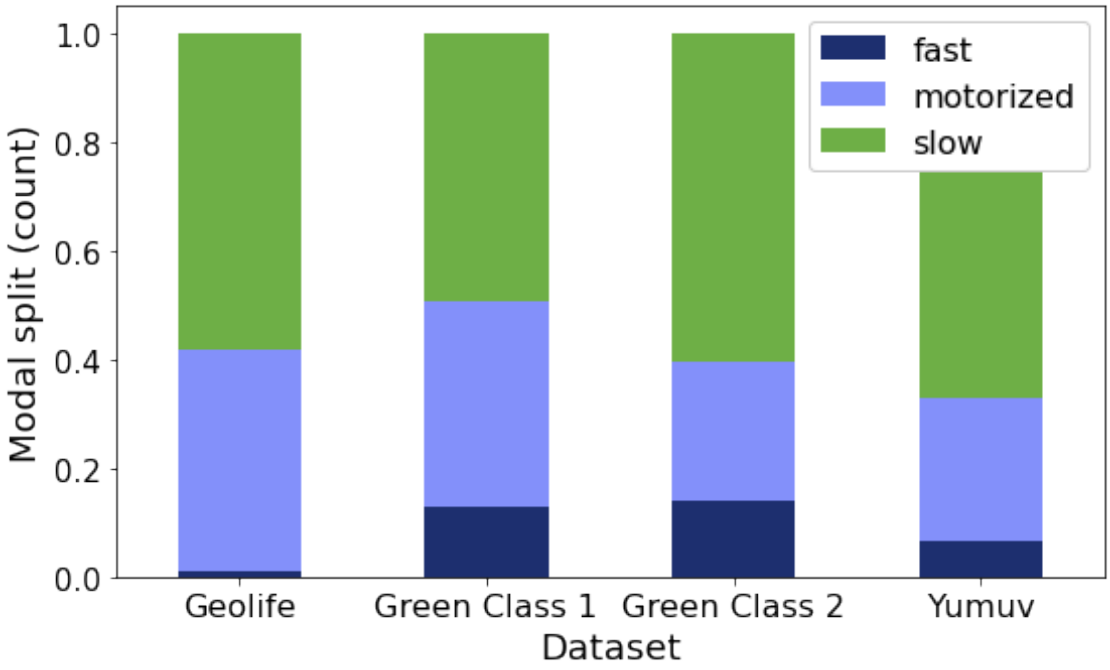
[100]:
```
mode               fast  motorized      slow
study
Geolife        0.627340   0.297629  0.075030
Green Class 1  0.539562   0.421444  0.038994
Green Class 2  0.701996   0.230656  0.067348
Yumuv          0.451134   0.443738  0.105128
```

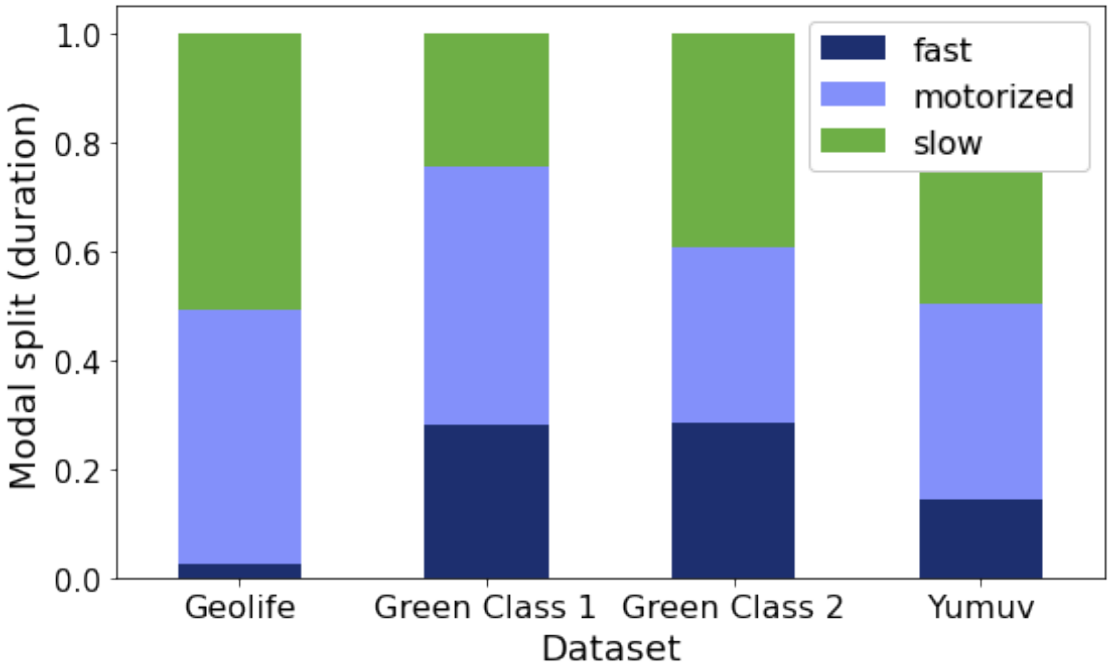
2.5.2 Plotting

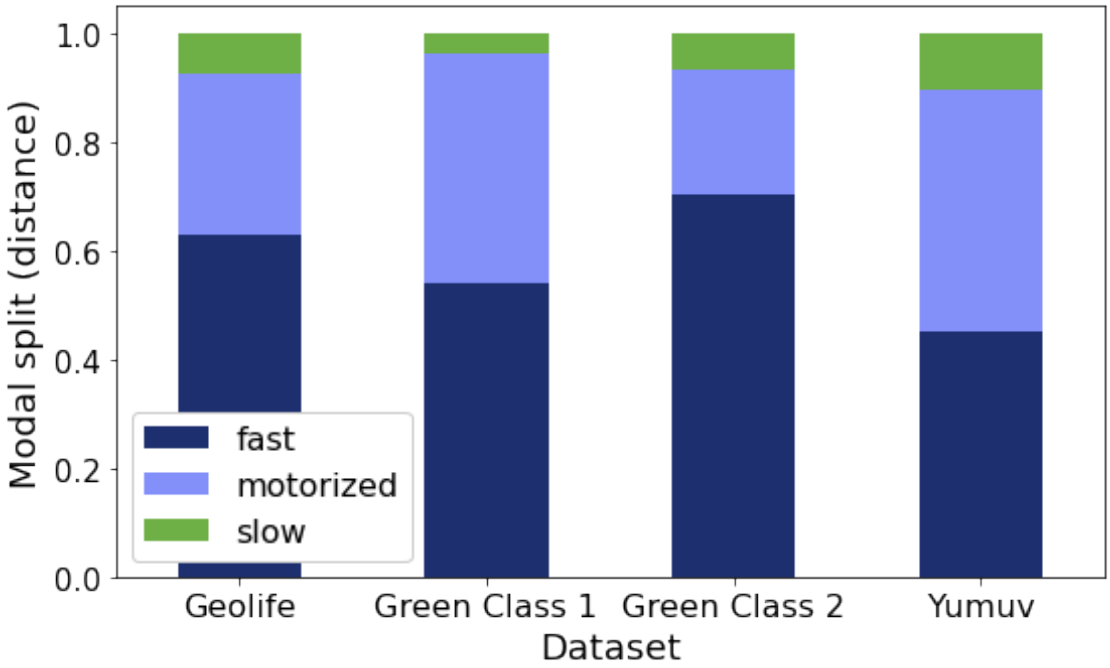
[245]:
```
colors = ["#1D2F6F", "#8390FA", "#6EAF46", "#FAC748"]
color = dict(zip(
    ["fast", "motorized", "slow"], ["#1D2F6F", "#8390FA", "#6EAF46"]
))


def plot_modal_split_comparison(split_type, modal_split_df):

    fig, ax = plt.subplots(figsize=(8, 5))
    modal_split_df.plot.bar(stacked=True, color=color, ax=ax)
    fs = 16
    legend_loc = "lower left" if split_type=="distance" else "upper right"
    plt.legend(loc=legend_loc, framealpha=1, fontsize=fs)
    plt.xlabel("Dataset", fontsize=fs+2)
    plt.ylabel(f"Modal split ({split_type})", fontsize=fs+2)
    plt.xticks(fontsize=fs, rotation=0)
    plt.tight_layout()
    plt.savefig(os.path.join(
        out_path, f"modal_split_all_{split_type}.pdf"
```

```
    ), bbox_inches="tight")
    plt.show()
```

[246]:
```
# create plot for all modal split types
for split_type, modal_split_df in zip(
    ["count", "duration", "distance"],
    [modal_split_count, modal_split_duration, modal_split_distance],
):
    plot_modal_split_comparison(split_type, modal_split_df)
```




Modal split (duration)
1.0
0.8
0.6
0.4
0.2
0.0
fast
motorized
slow
Geolife
Green Class 1
Green Class 2
Yumuv
Dataset


Modal split (distance)
1.0
0.8
0.6
0.4
0.2
0.0
fast
motorized
slow
Geolife
Green Class 1
Green Class 2
Yumuv
Dataset

2.6 Home / Work labeling

In this section trackintel is used to analyze the activity patterns of participants of the different datasets. In the Green Class 1&2 datasets, the activity labels were provided by the participants. To analyze all datasets we'll first infer the major activity labels in the Geolife and yumuv dataset using the trackintel method `location_identifier`.

2.6.1 Compute staypoint purpose for Geolife and Yumuv

[106]:
```
yumuv_geolife_flag = staypoints["study"].isin(["Geolife", "Yumuv"])

staypoints.loc[yumuv_geolife_flag, "purpose"] = ti.analysis.location_identifier(
    staypoints.loc[yumuv_geolife_flag], pre_filter=False
)["purpose"]
```

2.6.2 Select work or home for analysis

In the following we will analyze the distribution of home or work activity staypoints over time. To chose the analysis, the variable `home_work_variable` is either set to "home" or "work"

[327]:
```
# Chose to analyze "home" or "work" activity staypoints
home_work_variable = "home"
```

2.6.3 Data preparation for plotting

[328]:
```
# Use either the home staypoints or the work staypoints
if home_work_variable == "home":
    sp_study = staypoints[staypoints["purpose"] == "home"].copy()
elif home_work_variable == "work":
    sp_study = staypoints[staypoints["purpose"] == "work"].copy()
```

[329]:
```
# convert timestamp columns
sp_study.loc[:, "started_at"] = sp_study.loc[
    :, "started_at"].dt.tz_convert("Europe/Paris")
sp_study.loc[:, "finished_at"] = sp_study.loc[
    :, "finished_at"].dt.tz_convert("Europe/Paris")
```

2.6.4 Data transformation

To create a nice plot, we calculate the density of home or work staypoints in every minute bin. For this the staypoints are resampled with a minute resolution and then later aggregated again.

[330]:
```
# chop up durations to minute-by-minute time series
sp_study = sp_study[["started_at", "finished_at", "study"]]

# create a column that contains date ranges with minute resolution
sp_study["date"] = sp_study.apply(
    lambda x: pd.date_range(
        x["started_at"], x["finished_at"], freq="min")
```

```
    , axis=1
)
sp_study_expl = sp_study.explode("date", ignore_index=True).drop(
    columns=["started_at", "finished_at"]
)
```

[331]:
```
# create hour & minute attributes used for aggregation later.
# Get Geolife in local time zone
geolife_flag = sp_study_expl["study"] == "Geolife"
sp_study_expl.loc[~geolife_flag, "hour"] = sp_study_expl.loc[
    ~geolife_flag, "date"
].dt.hour
sp_study_expl.loc[geolife_flag, "hour"] = sp_study_expl.loc[
    geolife_flag, "date"
].dt.tz_convert("Asia/Shanghai").dt.hour
sp_study_expl["minute"] = sp_study_expl.date.dt.minute
sp_study_expl["day"] = sp_study_expl.date.dt.date
sp_study_expl.head(3)
```

[331]:

	study	date	hour	minute	day
0	Geolife	2009-03-30 08:20:40+02:00	14.0	20	2009-03-30
1	Geolife	2009-03-30 08:21:40+02:00	14.0	21	2009-03-30
2	Geolife	2009-03-30 08:22:40+02:00	14.0	22	2009-03-30

[332]:
```
# aggregate by hour and minute of every day for every study
count_by_minute = pd.DataFrame(sp_study_expl.groupby(
    ["study", "day", "hour", "minute"]
).size()).rename({0: "nr_home_sp"}, axis=1)
```

[333]:
```
count_by_minute.reset_index(inplace=True)
count_by_minute["minute_of_day"] = count_by_minute[
    "hour"] * 60 + count_by_minute["minute"]
count_by_minute.head(3)
```

[333]:

	study	minute_of_day	users_at_home
0	Geolife	0.0	0.520938
1	Geolife	1.0	0.520791
2	Geolife	2.0	0.520882

[334]:
```
count_by_minute.tail(3)
```

[334]:

	study	minute_of_day	users_at_home
5757	Yumuv	1437.0	0.676193
5758	Yumuv	1438.0	0.676623
5759	Yumuv	1439.0	0.677077

2.6.5 Normalize: Fraction of users at home/work for each minute

[335]:
```
# Get the active number of users per day
active_users_per_day = staypoints.set_index("started_at").groupby(
    ["study", "user_id", pd.Grouper(freq="D")]
).size().reset_index()
active_users_per_day["day"] = active_users_per_day["started_at"].dt.date
active_users_per_day = active_users_per_day.groupby(
    ["study", "day"]
).size().reset_index().rename({0:"active_users"}, axis=1)
active_users_per_day.head(3)
```

[335]:

	study	day	active_users
0	Geolife	2007-04-12	3
1	Geolife	2007-04-13	4
2	Geolife	2007-04-14	3

[336]:
```
count_by_minute = count_by_minute.merge(
    active_users_per_day, left_on=["study", "day"],
    right_on=["study", "day"]
)
```

[337]:
```
# compute the number of users at home per day
count_by_minute["users_at_home"] = count_by_minute[
    "nr_home_sp"] / count_by_minute["active_users"]
```

[338]:
```
# Aggregate over the days to get the average fraction of users at hoe
count_by_minute = count_by_minute.groupby(
    ["study", "minute_of_day"]
).agg({"users_at_home": "mean"}).reset_index()
```

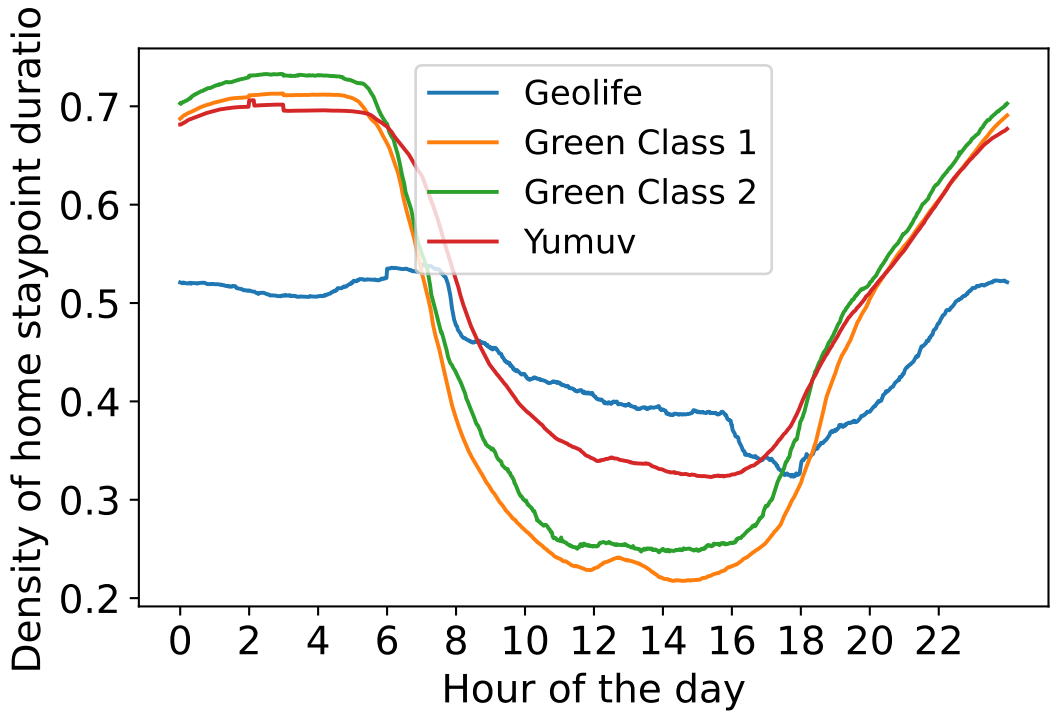
2.6.6 Plotting

[339]:
```
# reshape and normalize so that we can plot easily
count_by_minute_pivot = count_by_minute.pivot_table(
    columns="study", index="minute_of_day", values="users_at_home"
)
count_by_minute_pivot.head(3)
```

[339]:

study minute_of_day	Geolife	Green Class 1	Green Class 2	Yumuv
0.0	0.520938	0.687393	0.702919	0.681459
1.0	0.520791	0.687979	0.702329	0.681473
2.0	0.520882	0.688507	0.702768	0.681858

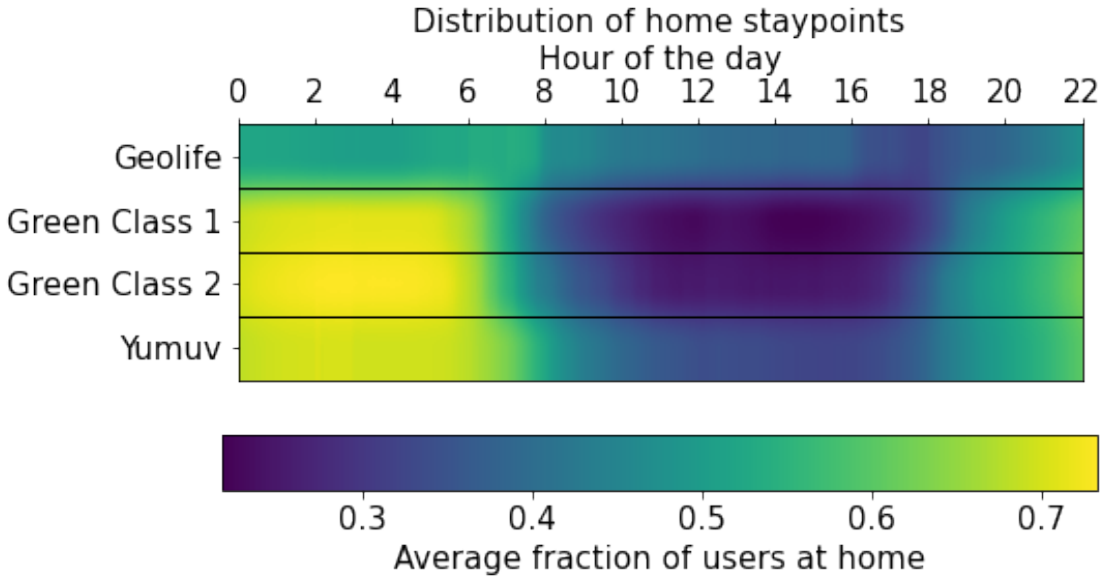
[340]:
```
count_by_minute_pivot.plot()
plt.xticks(
    np.arange(0, len(count_by_minute_pivot.index), 120), np.arange(0, 24, 2)
)
plt.legend(loc="lower left")
plt.ylabel(f"Density of {home_work_variable} staypoint duration")
plt.xlabel("Hour of the day")
plt.savefig(os.path.join(
    out_path, f"plot_activity_distribution_{home_work_variable}.pdf"
))
plt.show()
```



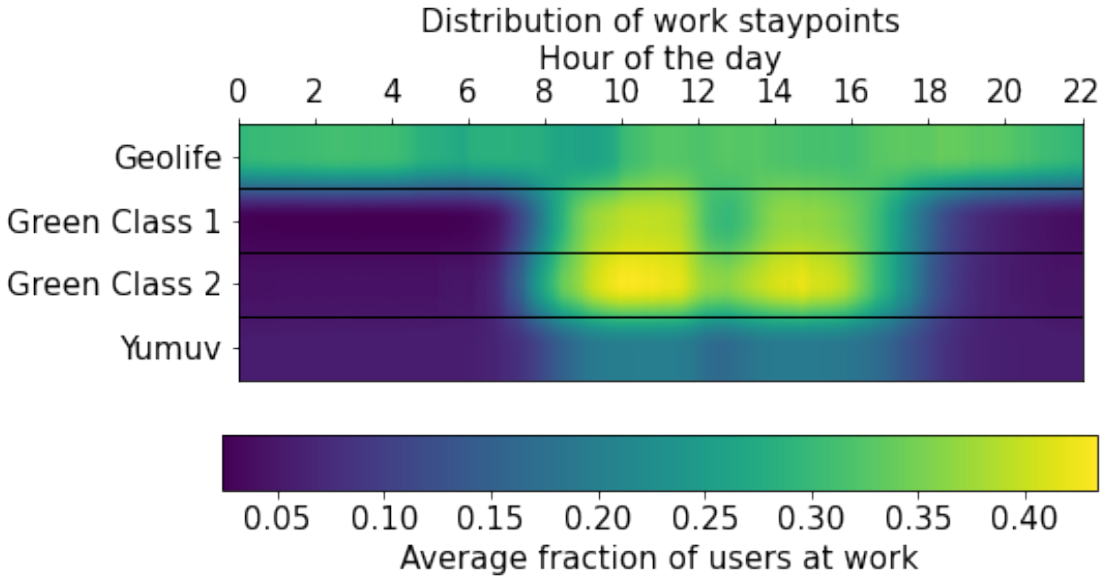
[341]:
```
def plot_work_home_labels(home_work_variable, count_by_minute_pivot, fs=15):
    fig, ax = plt.subplots(figsize=(12, 4))
    home_slots = count_by_minute_pivot.values.transpose()
    plt.imshow(home_slots, aspect=100)
    for i in range(4):
        plt.plot([0, home_slots.shape[1]], [i + 0.5, i + 0.5], c="black", lw=1)
    plt.xlim(0, 24)
    plt.yticks(np.arange(4), count_by_minute_pivot.columns, fontsize=fs)
    plt.xlabel("Hour of the day", fontsize=fs)
    ax.xaxis.tick_top()
    ax.xaxis.tickpad = -2
```

```
    ax.xaxis.set_label_position("top")
    plt.xticks(
        np.arange(0, len(count_by_minute_pivot.index), 120), np.arange(0, 24, 2),
        fontsize=fs
    )
    cbar = plt.colorbar(orientation="horizontal", ax=ax, aspect=16)
    cbar.set_label(f"Average fraction of users at {home_work_variable}",
                   fontsize=fs)
    cbar.ax.tick_params(labelsize=fs)
    plt.tight_layout()
    plt.savefig(
        os.path.join(
            out_path, f"imshow_act_distribution_{home_work_variable}.pdf"
        ),
        bbox_inches="tight",
    )
    plt.title(f"Distribution of {home_work_variable} staypoints", fontsize=fs)
    plt.show()
```

[342]:
```
# Execute all cells from this section with home_work_variable="home"
plot_work_home_labels("home", count_by_minute_pivot)
```



[326]:
```
# Execute all cells from this section with home_work_variable="work"
plot_work_home_labels("work", count_by_minute_pivot)
```



2.7 Visualization for individual users - Tracking data

Trackintel can also be used to visualize tracking data of individual users

2.7.1 Data collection

[275]:
```
x_min = 116.2
x_max = 116.5
y_min = 39.8
y_max = 40.1
sw = Point(x_min, y_min)
se = Point(x_max, y_min)
ne = Point(x_max, y_max)
nw = Point(x_min, y_max)

study_area = gpd.GeoDataFrame(
    columns=["geometry"],
    data=[Polygon([sw, se, ne, nw])],
    geometry="geometry",
    crs="EPSG:4326",
)
```

[276]:
```
# Load Geolife data of one user
tpls_vis = triplegs[triplegs["user_id"] == "51"].copy()
tpls_vis = ti.preprocessing.filter.spatial_filter(
    tpls_vis, study_area, method="within"
)
```

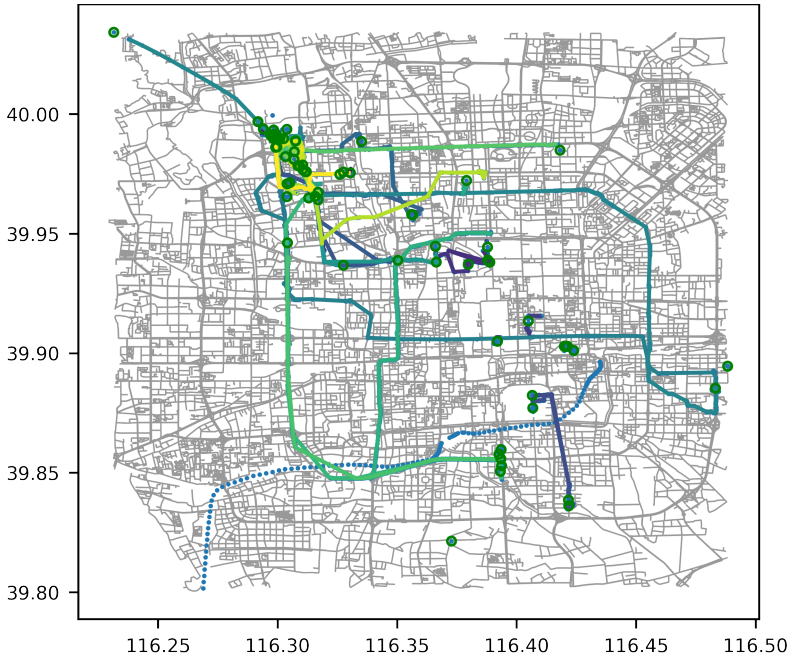
[277]:
```
# Get staypoints as well for this user
sp_vis = staypoints[staypoints["user_id"] == "51"].copy()
sp_vis = ti.preprocessing.filter.spatial_filter(
    sp_vis, study_area, method="within"
)
```

[278]:
```
# Get positionfixes for this user -
# using the pfs obtained with read_geolife function (see top of notebook)
pfs_vis = pfs_geolife[pfs_geolife["user_id"] == 51]
pfs_vis = ti.preprocessing.filter.spatial_filter(
    pfs_vis, study_area, method="within"
)
```

2.7.2 Plot all tracking data

[279]:
```
ti.visualization.plot_triplegs(
    tpls_vis,
    staypoints=sp_vis,
    plot_osm=True,
    positionfixes=pfs_vis,
    staypoints_radius=150,
    out_filename=os.path.join(out_path, "geolife_tpls_sp_pfs"),
)
Image(filename=os.path.join(
    out_path, "geolife_tpls_sp_pfs.png"
), width=600, height=600)
```

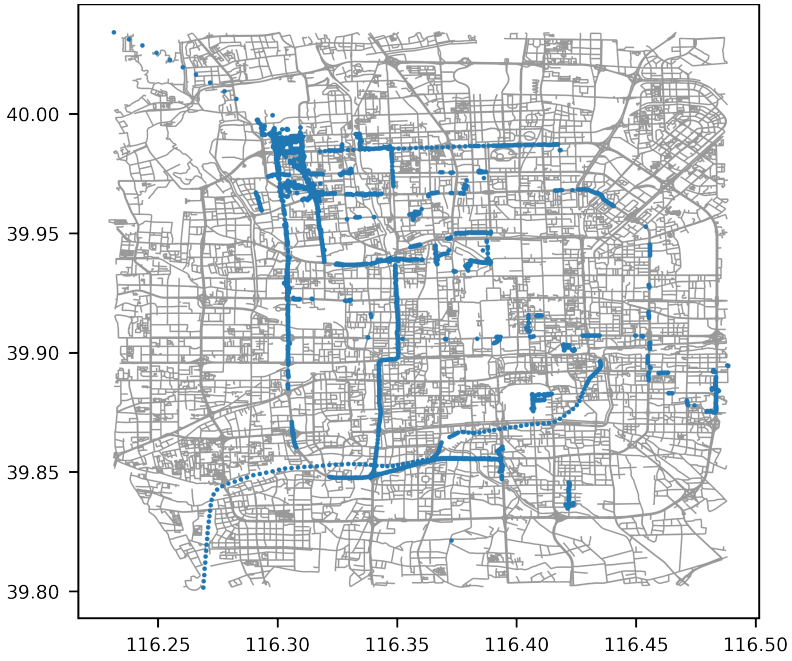
[279]:



2.7.3 Plot only positionfixes

[280]:
```
ti.visualization.plot_positionfixes(
    pfs_vis, plot_osm=True, out_filename=os.path.join(out_path, "geolife_pfs")
)
Image(
    filename=os.path.join(out_path, "geolife_pfs.png"), width=500, height=500
)
```

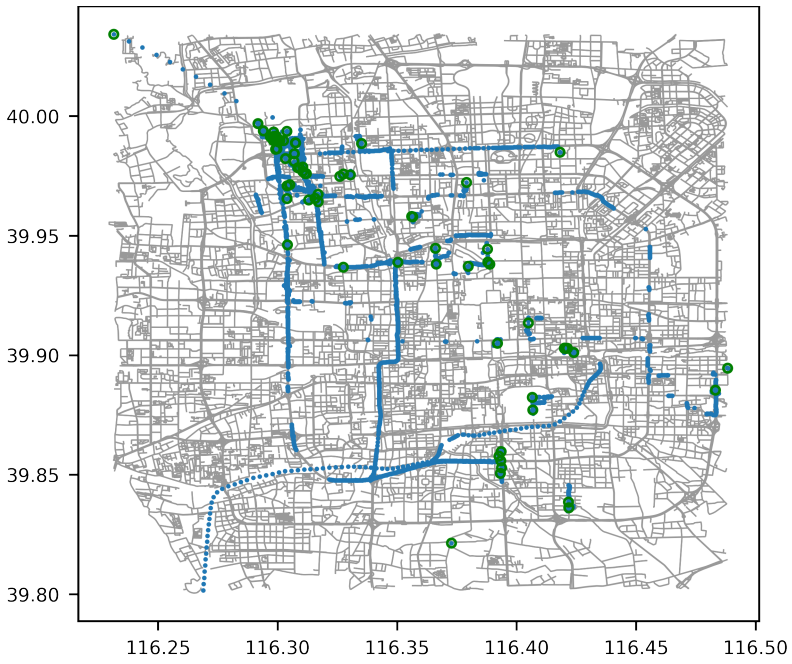
[280]:



2.7.4 Plot staypoints with positionfixes

[281]:
```
ti.visualization.plot_staypoints(
    sp_vis,
    positionfixes=pfs_vis,
    plot_osm=True,
    radius=150,
    out_filename=os.path.join(out_path, "geolife_sp_pfs"),
)
Image(filename=os.path.join(
    out_path, "geolife_sp_pfs.png"
), width=500, height=500)
```

[281]:



2.8 Visualization of individual users - Modal split

[282]:
```
# Use one GC2 user for this visualization
tpls_vis = triplegs[
    triplegs["user_id"] == "c9aa08e2-1a5d-4d41-ae62-6110a9072b23"
].copy()
```

[283]:
```
# rename to mode
tpls_vis["mode"] = tpls_vis["mode_detailed"]
```

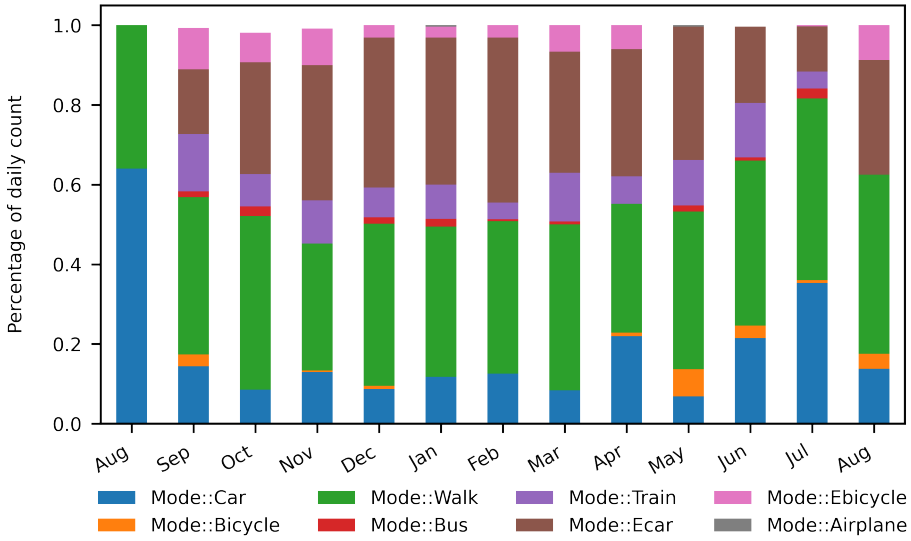
2.8.1 Modal split - by count

[284]:
```
# compute modal split
modal_split = calculate_modal_split(
    tpls_vis, freq="M", metric="count", per_user=False, norm=True
)
```

[285]:
```
# order the transport modes for colour choices
column_order = [
    "Mode::Car",
    "Mode::Bicycle",
    "Mode::Walk",
    "Mode::Bus",
    "Mode::Train",
    "Mode::Ecar",
    "Mode::Ebicycle",
```

```
    "Mode::Airplane",
]
modal_split = modal_split[column_order]
```

[286]:
```
fig, ax = plt.subplots(figsize=(5, 3))
ax = ti.visualization.modal_split.plot_modal_split(
    modal_split,
    date_fmt_x_axis="%b",
    y_label="Percentage of daily count",
    skip_xticks=0,
    n_col_legend=4,
    fig=fig,
    axis=ax,
    borderaxespad=2,
)
# fig.autofmt_xdate()
plt.savefig(os.path.join(out_path, "modal_split_count"))
```



2.8.2 Modal split - by distance

[287]:
```
modal_split = calculate_modal_split(
    tpls_vis, freq="M", metric="distance", per_user=False, norm=True
)
modal_split = modal_split[column_order]
```

[288]:
```
fig, ax = plt.subplots(figsize=(5, 3))
ax = ti.visualization.modal_split.plot_modal_split(
    modal_split,
```

```
    date_fmt_x_axis="%b",
    y_label="Percentage of daily distance",
    skip_xticks=0,
    n_col_legend=4,
    fig=fig,
    axis=ax,
    borderaxespad=2,
)
# fig.autofmt_xdate()
plt.savefig(os.path.join(out_path, "modal_split_distance"))
```