bmm

Release 1.1

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CONTENTS

`bmm` provides map-matching with uncertainty quantification for both online and offline inference!

Map-matching converts a series of noisy GPS coordinates into a continuous trajectory that is restricted to a graph (i.e. road network) or in the case of `bmm` a collection of continuous trajectories representing multiple plausible routes!

`bmm` is built on top of `osmnx`, an awesome package for retrieving and processing OpenStreetMap data.

The probabilistic model and particle smoothing methodology behind `bmm` can be found on arXiv and the source code on GitHub.

CHAPTER

ONE

DOCS

1.1 Functions

bmm.**offline_map_match**(*graph*, *polyline*, *n_samps*, *timestamps*, *mm_model=<bmm.ExponentialMapMatchingModel object>*, *proposal_func=<function optimal_proposal>*, *d_refine=1*, *initial_d_truncate=None*, *max_rejections=20*, *ess_threshold=1*, *store_norm_quants=False*, *store_filter_particles=False*, *verbose=True*, ***kwargs*)

Runs offline map-matching, i.e. receives a full polyline and returns an equal probability collection of trajectories. Forward-filtering backward-simulation implementation - no fixed-lag approximation needed for offline inference.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **polyline** (*numpy.ndarray*) – series of cartesian cooridnates in UTM
- **n_samps** (*int*) – int number of particles
- **timestamps** (*Union[float, numpy.ndarray]*) – seconds either float if all times between observations are the same, or a series of timestamps in seconds/UNIX timestamp
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel
- **proposal_func** (*Callable*) – function to propagate and weight single particle defaults to optimal (discretised) proposal
- **d_refine** (*int*) – metres, resolution of distance discretisation
- **initial_d_truncate** (*Optional[float]*) – distance beyond which to assume zero likelihood probability at time zero defaults to 5 * mm_model.gps_sd
- **max_rejections** (*int*) – number of rejections to attempt before doing full fixed-lag stitching 0 will do full fixed-lag stitching and track ess_stitch
- **ess_threshold** (*float*) – in [0,1], particle filter resamples if ess < ess_threshold * n_samps
- **store_norm_quants** (*bool*) – if True normalisation quantities (including gradient evals) returned in out_particles
- **store_filter_particles** (*bool*) – if True filter particles returned in out_particles
- **verbose** (*bool*) – bool whether to print ESS at each iterate
- **kwargs** – optional parameters to pass to proposal i.e. d_max, d_refine or var as well as ess_threshold for backward simulation update

Returns MMParticles object

Return type *bmm.MMParticles*

bmm.**initiate_particles**(*graph*, *first_observation*, *n_samps*, *mm_model=<bmm.ExponentialMapMatchingModel object>*, *d_refine=1*, *d_truncate=None*, *ess_all=True*, *filter_store=True*)

Initiate start of a trajectory by sampling points around the first observation. Note that coordinate system of inputs must be the same, typically a UTM projection (not longtitude-latitude!).

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel
- **first_observation** (*numpy.ndarray*) – cartesian coordinate in UTM
- **n_samps** (*int*) – number of samples to generate
- **d_refine** (*float*) – metres, resolution of distance discretisation
- **d_truncate** (*Optional[float]*) – metres, distance beyond which to assume zero likelihood probability defaults to 5 * mm_model.gps_sd
- **ess_all** (*bool*) – if true initiate effective sample size for each particle for each observation otherwise initiate effective sample size only for each observation
- **filter_store** (*bool*) – whether to initiate storage of filter particles and weights

Returns MMParticles object

Return type *bmm.MMParticles*

bmm.**update_particles**(*graph*, *particles*, *new_observation*, *time_interval*, *mm_model=<bmm.ExponentialMapMatchingModel object>*, *proposal_func=<function optimal_proposal>*, *update='BSi'*, *lag=3*, *max_rejections=20*, ***kwargs*)

Updates particle approximation in receipt of new observation

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **particles** (bmm.MMParticles) – unweighted particle approximation up to the previous observation time
- **new_observation** (*numpy.ndarray*) – cartesian coordinate in UTM
- **time_interval** (*float*) – time between last observation and newly received observation
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel
- **proposal_func** (*Callable*) – function to propagate and weight single particle
- **update** (*str*) –
  - 'PF' for particle filter fixed-lag update
  - 'BSi' for backward simulation fixed-lag update

  must be consistent across updates
- **lag** (*int*) – fixed lag for resampling/stitching

- **max_rejections** (*int*) – number of rejections to attempt before doing full fixed-lag stitching 0 will do full fixed-lag stitching and track ess_stitch
- **kwargs** – optional parameters to pass to proposal i.e. d_max, d_refine or var as well as ess_threshold for backward simulation update

Returns MMParticles object

Return type *bmm.MMParticles*

bmm.**_offline_map_match_fl**(*graph*, *polyline*, *n_samps*, *timestamps*, *mm_model=<bmm.ExponentialMapMatchingModel object>*, *proposal_func=<function optimal_proposal>*, *update='BSi'*, *lag=3*, *d_refine=1*, *initial_d_truncate=None*, *max_rejections=20*, *verbose=True*, ***kwargs*)

Runs offline map-matching but uses online fixed-lag techniques. Only recommended for simulation purposes.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **polyline** (*numpy.ndarray*) – series of cartesian coordinates in UTM
- **n_samps** (*int*) – int number of particles
- **timestamps** (*Union[float, numpy.ndarray]*) – seconds, either float if all times between observations are the same, or a series of timestamps in seconds/UNIX timestamp
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel
- **proposal_func** (*Callable*) – function to propagate and weight single particle defaults to optimal (discretised) proposal
- **update** (*str*) –
  - 'PF' for particle filter fixed-lag update
  - 'BSi' for backward simulation fixed-lag update

  must be consistent across updates
- **lag** (*int*) – fixed lag for resampling/stitching
- **d_refine** (*int*) – metres, resolution of distance discretisation
- **initial_d_truncate** (*Optional[float]*) – distance beyond which to assume zero likelihood probability at time zero, defaults to 5 * mm_model.gps_sd
- **max_rejections** (*int*) – number of rejections to attempt before doing full fixed-lag stitching, 0 will do full fixed-lag stitching and track ess_stitch
- **verbose** (*bool*) – bool whether to print ESS at each iterate
- **kwargs** – optional parameters to pass to proposal i.e. d_max or var as well as ess_threshold for backward simulation update

Returns MMParticles object

Return type *bmm.MMParticles*

bmm.**sample_route**(*graph*, *timestamps*, *num_obs=None*, *mm_model=<bmm.ExponentialMapMatchingModel object>*, *d_refine=1.0*, *start_position=None*, *num_inter_cut_off=None*)

Runs offline map-matching. I.e. receives a full polyline and returns an equal probability collection of trajectories. Forward-filtering backward-simulation implementation - no fixed-lag approximation needed for offline inference.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **timestamps** (*Union[float, numpy.ndarray]*) – seconds either float if all times between observations are the same, or a series of timestamps in seconds/UNIX timestamp
- **num_obs** (*Optional[int]*) – int length of observed polyline to generate
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel
- **d_refine** (*float*) – metres, resolution of distance discretisation
- **start_position** (*Optional[numpy.ndarray]*) – optional start position; array (u, v, k, alpha)
- **num_inter_cut_off** (*Optional[int]*) – maximum number of intersections to cross in the time interval

Returns tuple with sampled route (array with same shape as a single MMParticles) and polyline (array with shape (num_obs, 2))

Return type *Tuple*[numpy.ndarray, numpy.ndarray]

bmm.**random_positions**(*graph*, *n=1*)

Sample random positions on a graph. :param graph: encodes road network, simplified and projected to UTM :param n: int number of positions to sample, default 1 :return: array of positions (u, v, key, alpha) - shape (n, 4)

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) –
- **n** (*int*) –

Return type numpy.ndarray

bmm.**offline_em**(*graph*, *mm_model*, *timestamps*, *polylines*, *save_path*, *n_ffbsi=100*, *n_iter=10*, *gradient_stepsize_scale=0.001*, *gradient_stepsize_neg_exp=0.5*, ***kwargs*)

Run expectation maximisation to optimise parameters of bmm.MapMatchingModel object. Updates the hyperparameters of mm_model in place.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **mm_model** (bmm.MapMatchingModel) – MapMatchingModel - of which parameters will be updated
- **timestamps** (*Union[list, float]*) – seconds, either float if all times between observations are the same, or a series of timestamps in seconds/UNIX timestamp, if timestamps given, must be of matching dimensions to polylines
- **polylines** (*list*) – UTM polylines
- **save_path** (*str*) – path to save learned parameters
- **n_ffbsi** (*int*) – number of samples for FFBSi algorithm
- **n_iter** (*int*) – number of EM iterations
- **gradient_stepsize_scale** (*float*) – starting stepsize
- **gradient_stepsize_neg_exp** (*float*) – rate of decay of stepsize, in [0.5, 1]
- **kwargs** – additional arguments for FFBSi

Returns dict of optimised parameters

bmm.**plot**(*graph*, *particles=None*, *polyline=None*, *label_start_end=True*, *bgcolor='white'*, *node_color='grey'*, *node_size=0*, *edge_color='lightgrey'*, *edge_linewidth=3*, *particles_color='orange'*, *particles_alpha=None*, *polyline_color='red'*, *polyline_s=100*, *polyline_linewidth=3*, ***kwargs*)

Plots particle approximation of trajectory

Parameters

- **graph** – NetworkX MultiDiGraph UTM projection encodes road network e.g. generated using OSMnx
- **particles** – MMParticles object (from inference.particles) particle approximation
- **polyline** – list-like, each element length 2 UTM - metres series of GPS coordinate observations
- **label_start_end** – bool whether to label the start and end points of the route
- **bgcolor** – str background colour
- **node_color** – str node (intersections) colour
- **node_size** – float size of nodes (intersections)
- **edge_color** – str colour of edges (roads)
- **edge_linewidth** – float width of edges (roads
- **particles_color** – str colour of routes
- **particles_alpha** – float in [0, 1] plotting parameter opacity of routes
- **polyline_color** – str colour of polyline crosses
- **polyline_s** – str size of polyline crosses
- **polyline_linewidth** – str linewidth of polyline crosses
- **kwargs** – additional parameters to ox.plot_graph

Returns fig, ax

bmm.**get_possible_routes**(*graph*, *in_route*, *dist*, *all_routes=False*, *num_inter_cut_off=inf*)

Given a route so far and maximum distance to travel, calculate and return all possible routes on graph.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **in_route** (*numpy.ndarray*) – shape = (_, 9) columns: t, u, v, k, alpha, x, y, n_inter, d t: float, time u: int, edge start node v: int, edge end node k: int, edge key alpha: in [0,1], position along edge x: float, metres, cartesian x coordinate y: float, metres, cartesian y coordinate d: metres, distance travelled
- **dist** (*float*) – metres, maximum possible distance to travel
- **all_routes** (*bool*) – if true return all routes possible <= d otherwise return only routes of length d
- **num_inter_cut_off** (*int*) – maximum number of intersections to cross in the time interval

Returns list of arrays each array with shape = (_, 9) as in_route each array describes a possible route

Return type list

bmm.**cartesianise_path**(*graph*, *path*, *t_column=True*, *observation_time_only=False*)

Converts particle or array of edges and alphas into cartesian (x,y) points.

Parameters

- **path** – numpy.ndarray, shape=(_, 5+) columns - (t), u, v, k, alpha, ...
- **t_column** – boolean boolean describing if input has a first column for the time variable

Returns numpy.ndarray, shape = (_, 2) cartesian points

bmm.**get_geometry**(*graph*, *edge*)

Extract geometry of an edge from global graph object. If geometry doesn't exist set to straight line.

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **edge** (*numpy.ndarray*) – length = 3 with elements u, v, k * u: int, edge start node * v: int, edge end node * k: int, edge key

Returns edge geometry

Return type shapely.geometry.linestring.LineString

bmm.**discretise_edge**(*graph*, *edge*, *d_refine*)

Discretises edge to given edge refinement parameter. Returns array of proportions along edge, xy cartesian coordinates and distances along edge

Parameters

- **graph** (*networkx.classes.multidigraph.MultiDiGraph*) – encodes road network, simplified and projected to UTM
- **edge** (*numpy.ndarray*) – list-like, length = 3 with elements u, v, k * u: int, edge start node * v: int, edge end node * k: int, edge key
- **d_refine** (*float*) – metres, resolution of distance discretisation

Returns shape = (_, 4) with columns * alpha: float in (0,1], position along edge * x: float, metres, cartesian x coordinate * y: float, metres, cartesian y coordinate * distance: float, distance from start of edge

Return type numpy.ndarray

bmm.**observation_time_indices**(*times*)

Remove zeros (other than the initial zero) from a series

Parameters **times** (*numpy.ndarray*) – series of timestamps

Returns bool array of timestamps that are either non-zero or the first timestamp

Return type numpy.ndarray

bmm.**observation_time_rows**(*path*)

Returns rows of path only at observation times (not intersections)

Parameters **path** (*numpy.ndarray*) – numpy.ndarray, shape=(_, 5+) columns - t, u, v, k, alpha, ...

Returns trimmed path numpy.ndarray, shape like path

Return type numpy.ndarray

bmm.**long_lat_to_utm**(*points*, *graph=None*)

Converts a collection of long-lat points to UTM :param points: points to be projected, shape = (N, 2) :param graph: optional graph containing desired crs in graph.graph['crs'] :return: array of projected points

Parameters **points** (*Union[list, numpy.ndarray]*) –

Return type numpy.ndarray

1.2 Classes

class bmm.**MMParticles**(*initial_positions*)

Class to store trajectories from a map-matching algorithm.

In particular, contains the `self.particles` object, which is a list of n arrays each with shape = (_, 8)

where _ represents the trajectory length (number of nodes that are either intersection or observation) and columns:

- t: seconds, observation time
- u: int, edge start node
- v: int, edge end node
- k: int, edge key
- alpha: in [0,1], position along edge
- x: float, metres, cartesian x coordinate
- y: float, metres, cartesian y coordinate
- d: float, metres, distance travelled since previous observation time

As well as some useful properties: * `self.n`: number of particles * `self.m`: number of observations * `self.observation_times`: array of observation times * `self.latest_observation_time`: time of most recently received observation * `self.route_nodes`: list of length n, each element contains the series of nodes traversed for that particle

Initiate MMParticles storage of trajectories with some start positions as input.

Parameters **initial_positions** (*List[numpy.ndarray]*) – list, length = n_samps, each element is an array of length 6 with elements

- u: int, edge start node
- v: int, edge end node
- k: int, edge key
- alpha: in [0,1], position along edge
- x: float, metres, cartesian x coordinate
- y: float, metres, cartesian y coordinate

property latest_observation_time: float

Extracts most recent observation time. :return: time of most recent observation

property m: int

Number of observations received. :return: number of observations received

property observation_times: numpy.ndarray

Extracts all observation times. :return: array, shape = (m,)

route_nodes()

Returns n series of nodes describing the routes :return: length n list of arrays, shape (_,)

where _ represents the trajectory length (number of nodes that are either intersection or observation)

class bmm.**MapMatchingModel**

Class defining the state-space model used for map-matching.

Transition density (assuming constant time interval)

$$p(x_t, e_t|x_{t-1}) \propto \gamma(d_t) \exp(-\beta|d_t^{\text{gc}} - d_t|)\mathbb{1}[d_t < d_{\text{max}}],$$

where d_t is the distance between positions x_{t-1} and x_t along the series of edges e_{t-1}, restricted to the graph/road network. d_t^{gc} is the *great circle distance* between x_{t-1} and x_t, not restricted to the graph/road network.

The $\exp(-\beta|d_t^{\text{gc}} - d_t|)$ term penalises non-direct or windy routes where β is a parameter stored in `self.deviation_beta`, yet to be defined.

d_{max} is defined by `self.d_max` function (metres) and `self.max_speed` parameter (metres per second), defaults to 35.

The $\gamma(d_t)$ term penalises overly lengthy routes and is yet to be defined.

Observation density

$$p(y_t|x_t) = \mathcal{N}(y_t \mid x_t, \sigma^2_{\text{GPS}}\mathbb{I}_2),$$

where σ_{GPS} is the standard deviation (metres) of the GPS noise stored in `self.gps_sd`, yet to be defined. Additional optional `self.likelihood_d_truncate` for truncated Gaussian noise, defaults to inf.

The parameters `self.deviation_beta`, `self.gps_sd` and the distance prior parameters defined in `self.distance_params` and `self.distance_params_bounds` can be tuned using expectation-maximisation with `bmm.offline_em`.

For more details see https://arxiv.org/abs/2012.04602.

d_max(*time_interval*)

Initiates default value of the maximum distance possibly travelled in the time interval. Assumes a maximum possible speed.

Parameters **time_interval** (*float*) – float seconds time between observations

Returns float defaulted d_max

Return type float

deviation_prior_evaluate(*previous_cart_coord*, *route_cart_coords*, *distances*)

Evaluate deviation prior/transition density Vectorised to handle multiple evaluations at once :param previous_cart_coord: shape = (2,) or (_, 2) cartesian coordinate(s) at previous observation time :param route_cart_coords: shape = (_, 2), cartesian coordinates - positions along road network :param distances: shape = (_,) route distances between previous_cart_coord(s) and route_cart_coords :return: deviation prior density evaluation(s)

Parameters

- **previous_cart_coord** (*numpy.ndarray*) –
- **route_cart_coords** (*numpy.ndarray*) –
- **distances** (*numpy.ndarray*) –

Return type numpy.ndarray

distance_prior_bound(*time_interval*)

Extracts bound on the distance component of the prior/transition density :param time_interval: seconds, time between observations :return: bound on distance prior density

Parameters **time_interval** (*float*) –

Return type float

distance_prior_evaluate(*distance*, *time_interval*)

Evaluate distance prior/transition density Vectorised to handle multiple evaluations at once

Parameters

- **distance** (*Union[float, numpy.ndarray]*) – metres array if multiple evaluations at once
- **time_interval** (*Union[float, numpy.ndarray]*) – seconds, time between observations

Returns distance prior density evaluation(s)

Return type *Union*[float, numpy.ndarray]

distance_prior_gradient(*distance*, *time_interval*)

Evaluate gradient of distance prior/transition density in distance_params Vectorised to handle multiple evaluations at once

Parameters

- **distance** (*Union[float, numpy.ndarray]*) – metres array if multiple evaluations at once
- **time_interval** (*Union[float, numpy.ndarray]*) – seconds, time between observations

Returns distance prior density evaluation(s)

Return type *Union*[float, numpy.ndarray]

likelihood_evaluate(*route_cart_coords*, *observation*)

Evaluate probability of generating observation from cartesian coords Vectorised to evaluate over many cart_coords for a single observation Isotropic Gaussian with standard dev self.gps_sd :param route_cart_coords: shape = (_, 2), cartesian coordinates - positions along road network :param observation: shape = (2,) observed GPS cartesian coordinate :return: shape = (_,) likelihood evaluations

Parameters

- **route_cart_coords** (*numpy.ndarray*) –
- **observation** (*numpy.ndarray*) –

Return type *Union*[float, numpy.ndarray]

pos_distance_prior_bound(*time_interval*)

Extracts bound on the distance component of the prior/transition density given the distance is > 0 :param time_interval: seconds, time between observations :return: bound on distance prior density

Parameters **time_interval** (*float*) –

Return type float

class bmm.**ExponentialMapMatchingModel**(*zero_dist_prob_neg_exponent=0.133*, *lambda_speed=0.068*, *deviation_beta=0.052*, *gps_sd=5.23*)

Class defining the state-space model used for map-matching with exponential prior on distance travelled.

Transition density (assuming constant time interval)

$$p(x_t, e_t|x_{t-1}) \propto \gamma(d_t) \exp(-\beta|d_t^{\text{gc}} - d_t|)\mathbb{1}[d_t < d_{\text{max}}],$$

where d_t is the distance between positions x_{t-1} and x_t along the series of edges e_{t-1}, restricted to the graph/road network. d_t^{gc} is the *great circle distance* between x_{t-1} and x_t, not restricted to the graph/road network.

The $\exp(-\beta|d_t^{\text{gc}} - d_t|)$ term penalises non-direct or windy routes where β is a parameter stored in `self.deviation_beta` defaults to 0.052.

d_{max} is defined by `self.d_max` function (metres) and `self.max_speed` parameter (metres per second), defaults to 35.

The $\gamma(d_t)$ term

$$\gamma(d_t) = p^0 \mathbb{1}[d_t = 0] + (1 - p^0) \mathbb{1}[d_t > 0] \lambda \exp(-\lambda d_t / \Delta t),$$

penalises overly lengthy routes, defined as an exponential distribution with probability mass at $d_t = 0$ to account for traffic, junctions etc.

where $p^0 = \exp(-r^0 \Delta t)$ with Δt being the time interval between observations. The r^0 parameter is stored in `self.zero_dist_prob_neg_exponent` and defaults to 0.133. Exponential distribution parameter λ is stored in `self.lambda_speed` and defaults to 0.068.

Observation density

$$p(y_t|x_t) = \mathcal{N}(y_t \mid x_t, \sigma^2_{\text{GPS}} \mathbb{I}_2),$$

where σ_{GPS} is the standard deviation (metres) of the GPS noise stored in `self.gps_sd`, defaults to 5.23. Additional optional `self.likelihood_d_truncate` for truncated Gaussian noise, defaults to inf.

The parameters `self.deviation_beta`, `self.gps_sd` as well as the distance prior parameters `self.zero_dist_prob_neg_exponent` and `self.lambda_speed` can be tuned using expectation-maximisation with `bmm.offline_em`.

For more details see https://arxiv.org/abs/2012.04602.

Parameters

- **zero_dist_prob_neg_exponent** (*float*) – Positive parameter such that stationary probability is $p^0 = \exp(-r^0 \Delta t)$, defaults to 0.133.
- **lambda_speed** (*float*) – Positive parameter of exponential distribution over average speed between observations.
- **deviation_beta** (*float*) – Positive parameter of exponential distribution over route deviation.
- **gps_sd** (*float*) – Positive parameter defining standard deviation of GPS noise in metres.

distance_prior_bound(*time_interval*)

Extracts bound on the prior/transition density :param time_interval: seconds, time between observations :return: bound on distance prior density

Parameters **time_interval** (*float*) –

Return type float

distance_prior_evaluate(*distance*, *time_interval*)

Evaluate distance prior/transition density Vectorised to handle multiple evaluations at once

Parameters

- **distance** (*Union[float, numpy.ndarray]*) – metres array if multiple evaluations at once

- **time_interval** (*Union[float, numpy.ndarray]*) – seconds, time between observations

Returns distance prior density evaluation(s)

Return type *Union*[float, numpy.ndarray]

distance_prior_gradient(*distance*, *time_interval*)

Evaluate gradient of distance prior/transition density in distance_params Vectorised to handle multiple evaluations at once

Parameters

- **distance** (*Union[float, numpy.ndarray]*) – metres array if multiple evaluations at once
- **time_interval** (*Union[float, numpy.ndarray]*) – seconds, time between observations

Returns distance prior gradient evaluation(s)

Return type *Union*[float, numpy.ndarray]

pos_distance_prior_bound(*time_interval*)

Extracts bound on the distance component of the prior/transition density given the distance is > 0 :param time_interval: seconds, time between observations :return: bound on distance prior density

Parameters **time_interval** (*float*) –

Return type float

zero_dist_prob(*time_interval*)

Probability of travelling a distance of exactly zero :param time_interval: time between last observation and newly received observation :return: probability of travelling zero metres in time_interval

Parameters **time_interval** (*Union[float, numpy.ndarray]*) –

Return type *Union*[float, numpy.ndarray]

1.3 Index

CHAPTER

TWO

INSTALL

```
pip install bmm
```

CHAPTER

THREE

QUICKSTART

Load graph and convert to UTM (Universal Transverse Mercator), a commonly used projection of spherical longtitude-latitude coordinates into square x-y coordinates:

```
import numpy as np
import pandas as pd
import osmnx as ox
import json
import bmm

graph = ox.graph_from_place('Porto, Portugal')
graph = ox.project_graph(graph)
```

Beware that downloading graphs using `osmnx` can take a few minutes, especially for large cities.

Load polyline and convert to UTM:

```
data_path = 'simulations/porto/test_route.csv'
polyline_longlat = json.loads(pd.read_csv(data_path)['POLYLINE'][0])
polyline_utm = bmm.long_lat_to_utm(polyline_longlat, graph)
```

3.1 Offline map-matching

```
matched_particles = bmm.offline_map_match(graph, polyline=polyline_utm, n_samps=100,␣
↪timestamps=15)
```

3.2 Online map-matching

Initiate with first observation:

```
matched_particles = bmm.initiate_particles(graph, first_observation=polyline_utm[0], n_
↪samps=100)
```

Update when new observation comes in

```
matched_particles = bmm.update_particles(graph, matched_particles, new_
↪observation=polyline_utm[1], time_interval=15)
```

CHAPTER

FOUR

SANITY CHECK

You can manually test that bmm is working sensibly for a given graph by generating synthetic data:

```
graph = ox.graph_from_place('London, UK')
graph = ox.project_graph(graph)
generated_route, generated_polyline = bmm.sample_route(graph, timestamps=15, num_obs=20)
```

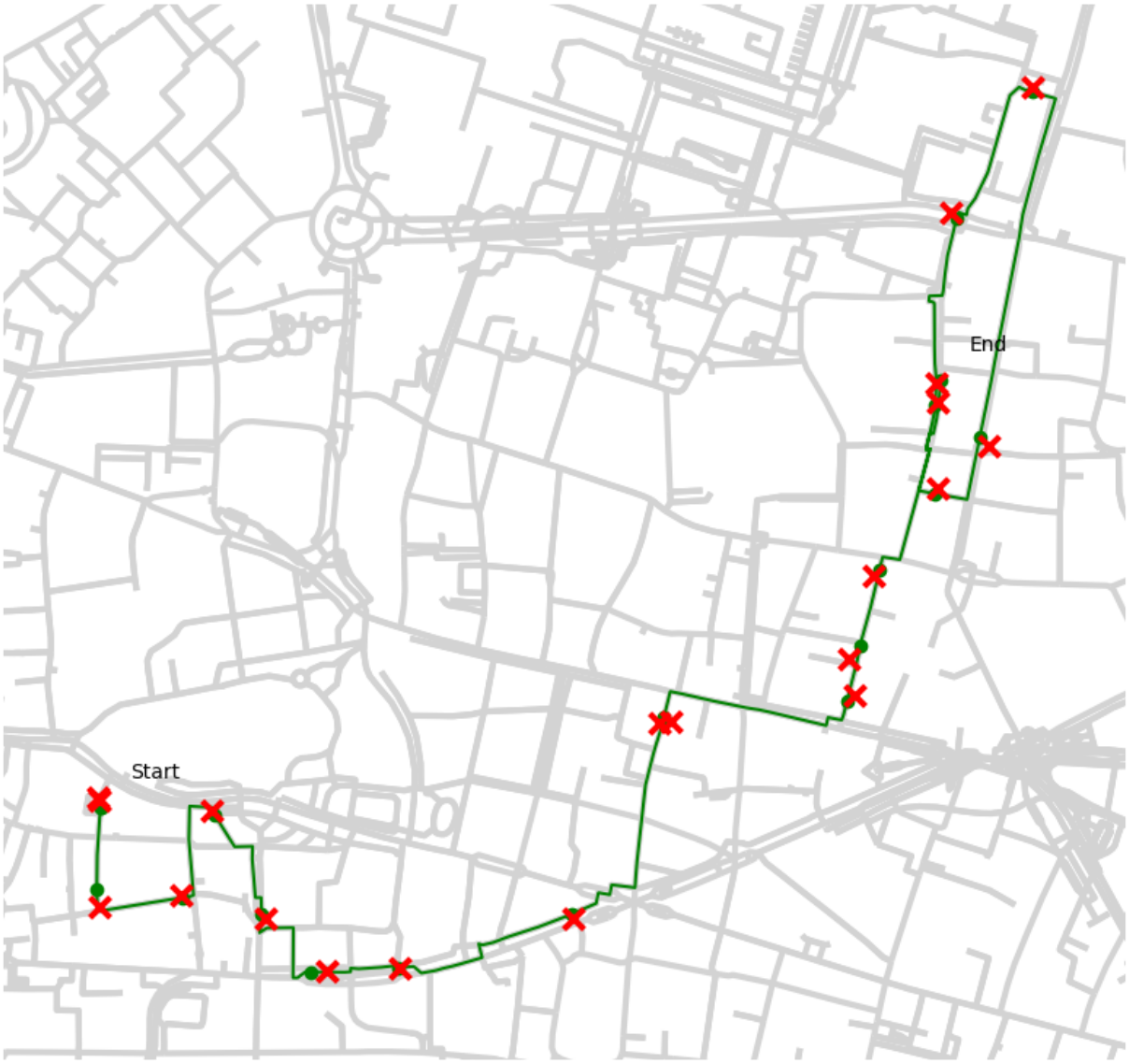
Note that the London graph takes some time (~10mins) to download and for testing on synthetic data it may be worth considering a smaller region (although not so small that the `sample_route` function consistently terminates early due to reaching the edge of the graph).

Run map-matching on the generated polyline:

```
matched_particles = bmm.offline_map_match(graph, generated_polyline, n_samps=100,␣
↪timestamps=15)
```

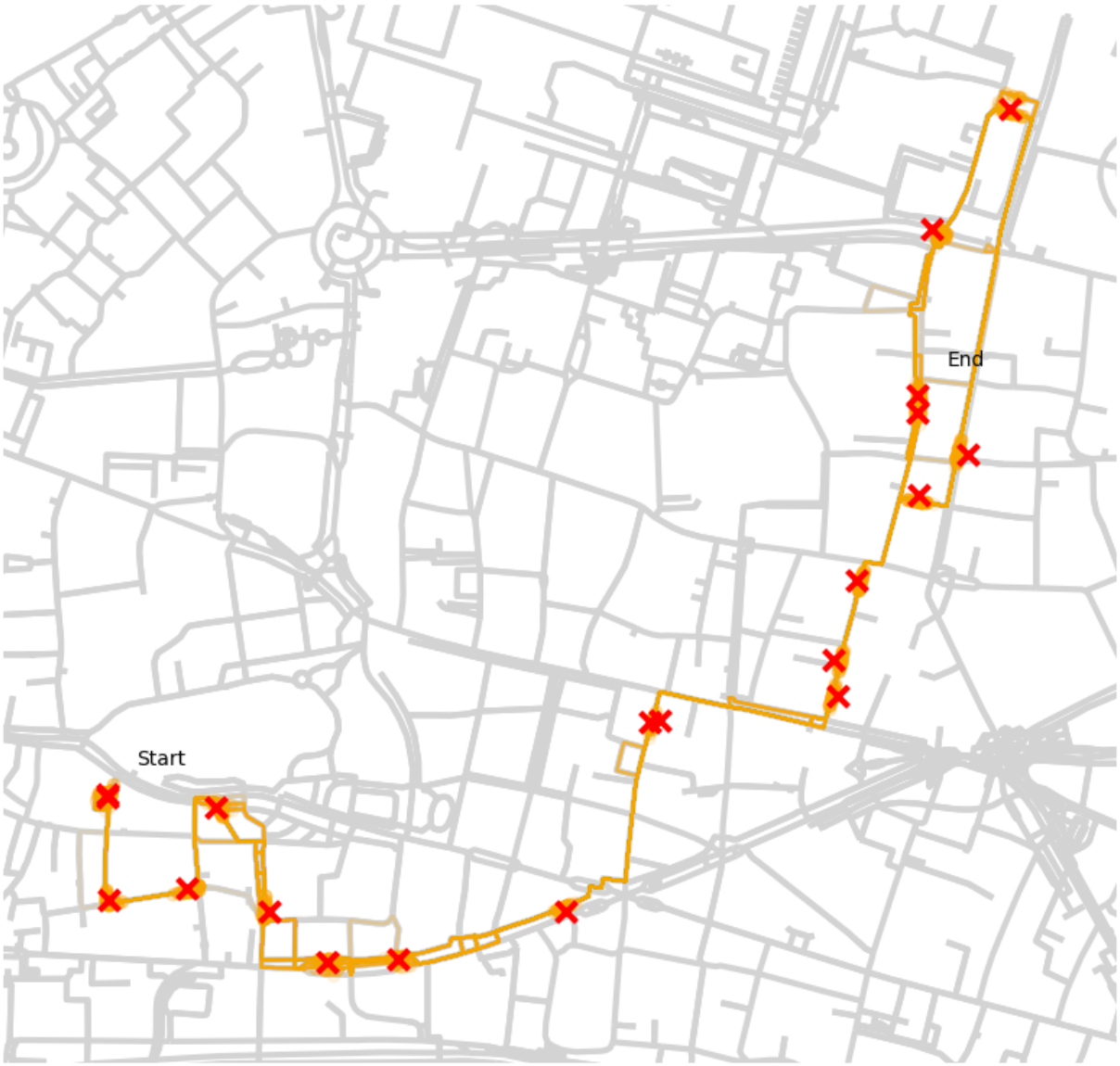
Plot true generated route:

```
bmm.plot(graph, generated_route, generated_polyline, particles_color='green')
```



Plot map-matched particles:

```
bmm.plot(graph, matched_particles, generated_polyline)
```


End
Start

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