Online Stochastic Prediction of Mid-Flight Aircraft Trajectories

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“uplifting the whole people”

— HENRY MARSHALL TORY, FOUNDING PRESIDENT, 1908

Agenda

1. Introduction
2. Online Trajectory Prediction using Hidden Markov Models
3. Experimental Evaluation
4. Acknowledgements

Motivation

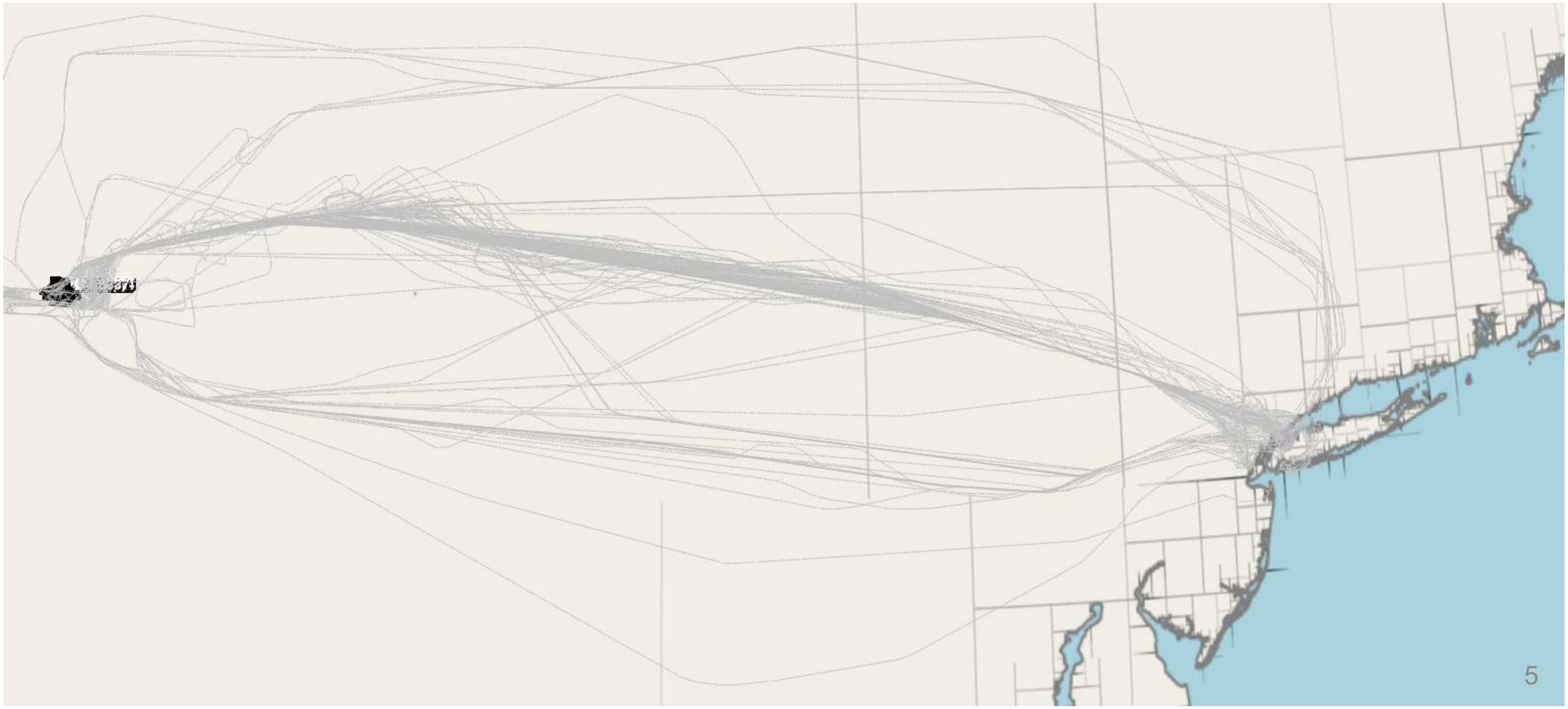
- Number of air travellers predicted to rise from 3.8 billion in 2016 to 7.2 billion by 2035
- Air Traffic Control (ATC) needs more accurate Trajectory Prediction (TP) systems
- Use of historical flight trajectory data in statistical modelling could improve prediction accuracy

Our Contribution

- Mapped basic concepts for the TP problem onto Hidden Markov Models (HMMs) that is able to incorporate local weather information
- Performed an extensive experimental evaluation using more than 16,000 historical trajectories over a continuous time span of 2 years
- Achieved an improvement of 26% in horizontal error and 32% in vertical error compared to two baseline models based on conventional approaches, while not requiring more prediction time

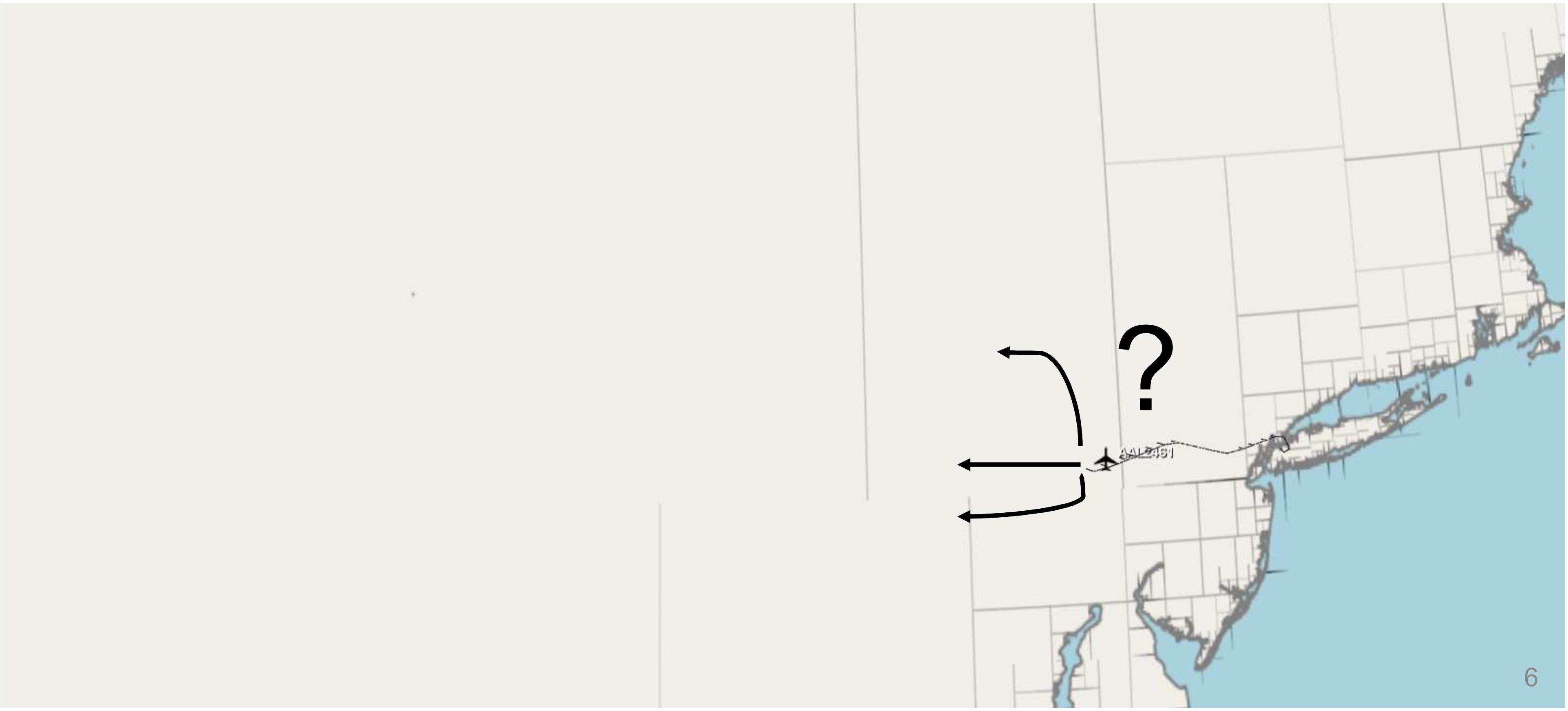
Problem Definition

- Given:



Problem Definition

- Find:



Our Approach

- Represent movement of aircraft as state changes along a Markov chain, and weather as observations, i.e. probabilistic functions of states
- Train transition probabilities using historical trajectories, and emission probabilities using weather parameters observed along these trajectories
- Use the HMM to predict the most probable trajectory, starting from the current state (i.e. position) of the aircraft

Geospatial Concepts

- *Definition 3.1.* A **geographical position** gp can be represented using 3 coordinates,

$$gp = (latitude, longitude, altitude)$$

- *Definition 3.2.* A **positional update** pos represents the geographical position gp of a particular aircraft at a particular timestamp ts,

$$pos = (gp, ts)$$

Geospatial Concepts

- *Definition 3.3.* A raw trajectory Trj_{ac} is a finite sequence of positional updates of a particular aircraft ac, over a sequence of timestamps, in increasing order,

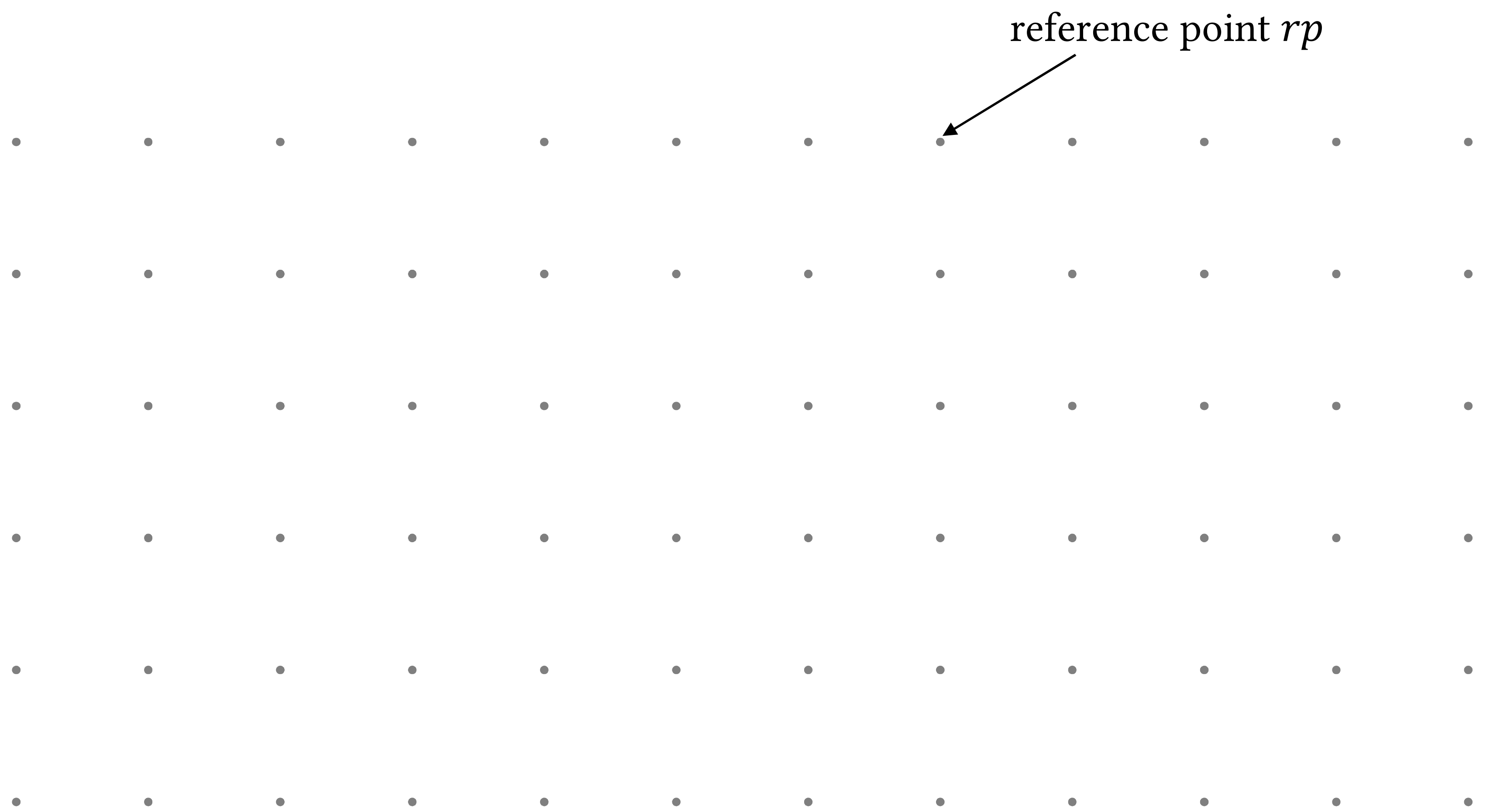
$$Trj_{ac} = (pos_1, \ldots, pos_n), n \in \mathbb{Z}^+, n \geq 2$$

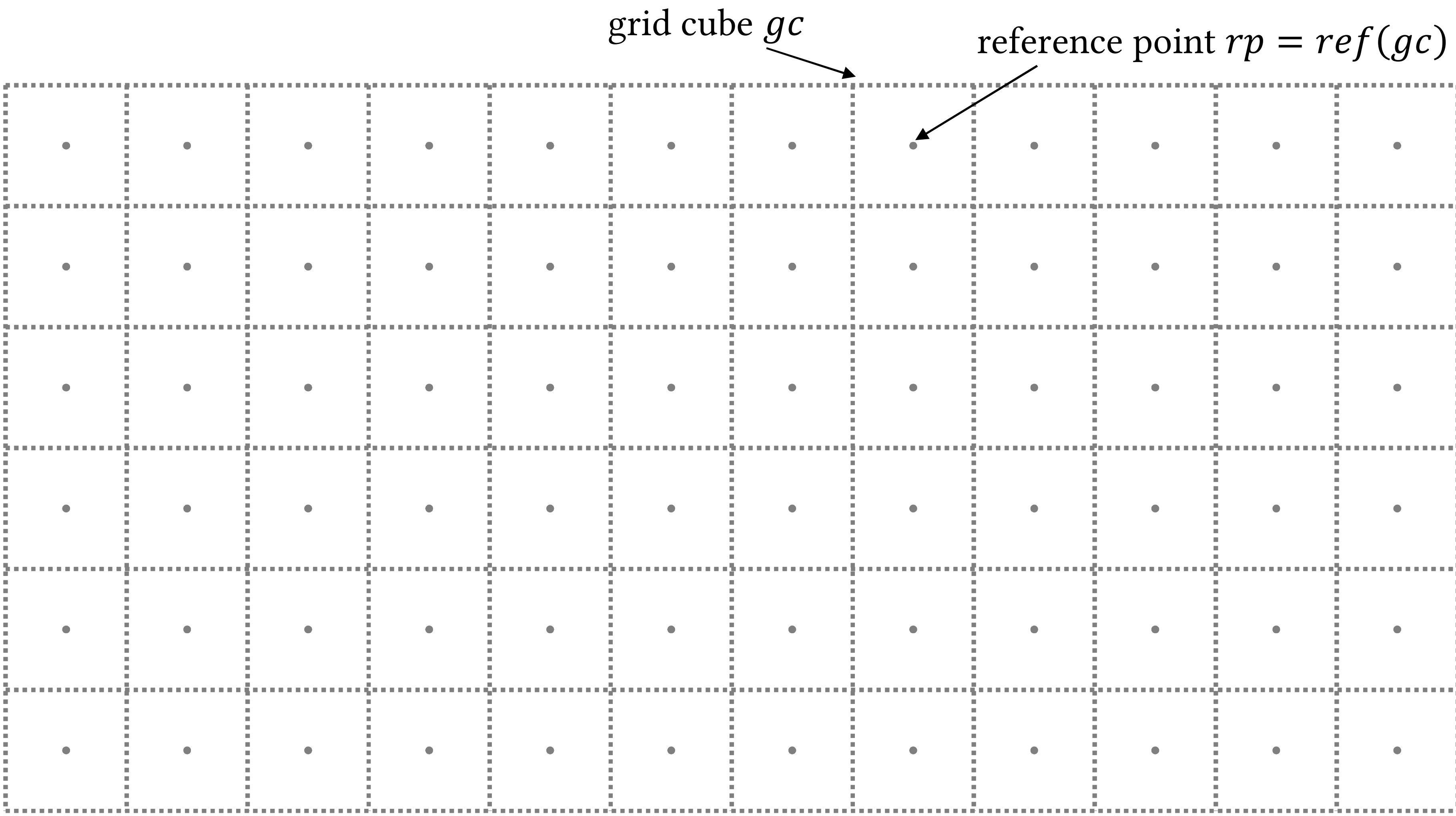
where each position is

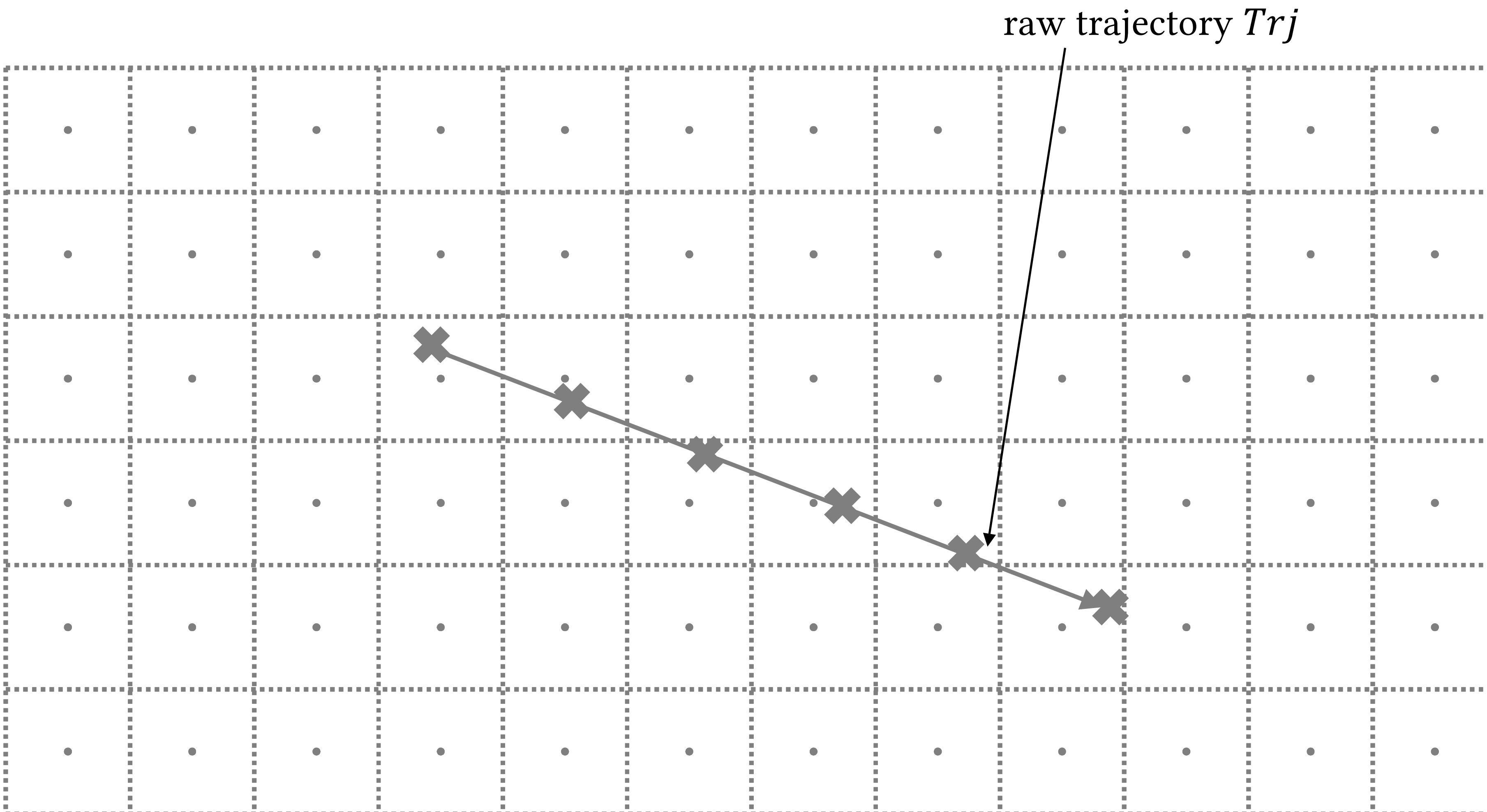
$$pos_i = (gp_i, ts_i), \forall i \in [1, n]$$

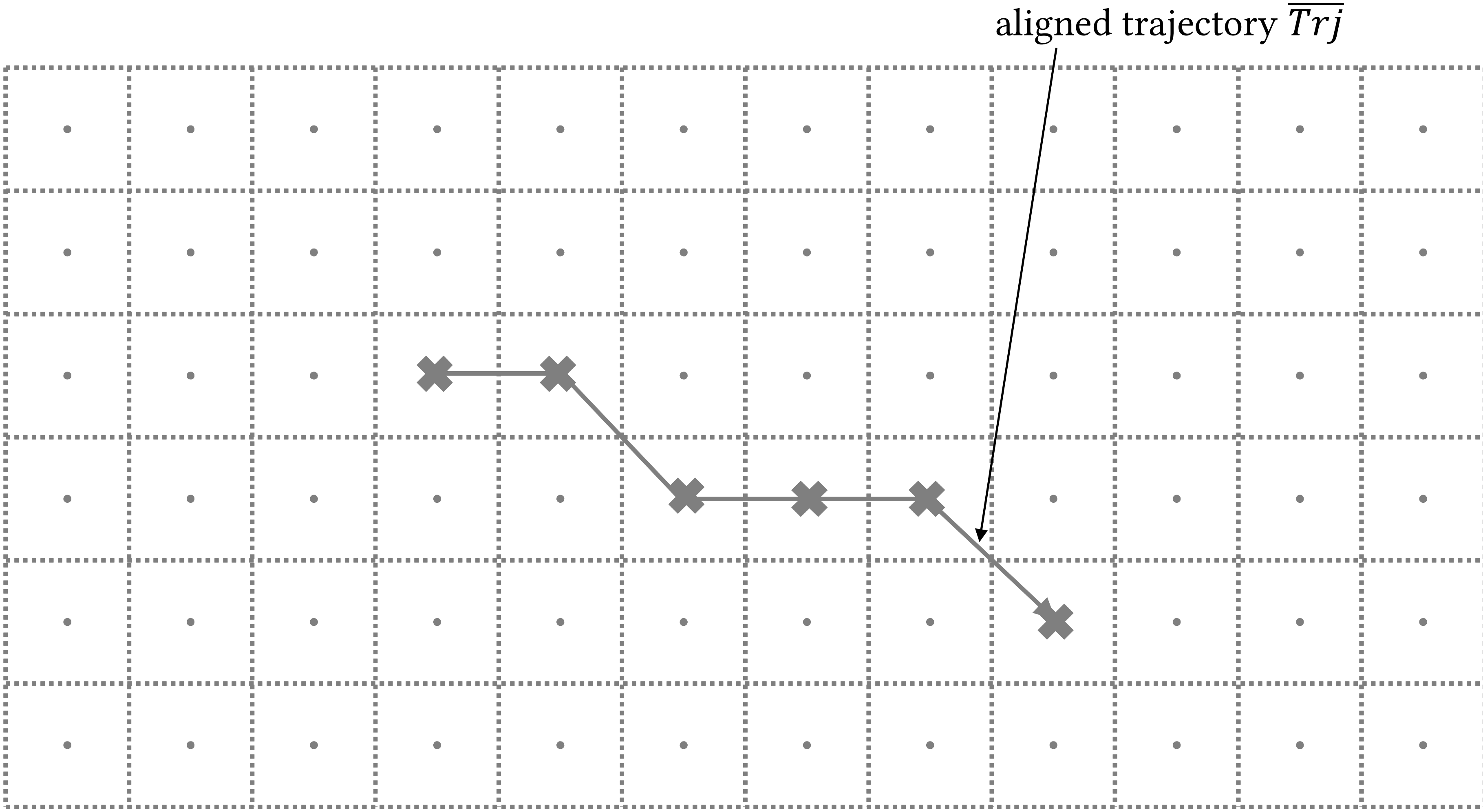
Reference Grid Concepts

- Horizontal dimension (latitude and longitude):
  - We use the planar reference grid of Rapid Refresh (RAP) consisting of reference points spaced 13.545km apart in a 451×337 configuration
- Vertical dimension (pressure altitude):
  - RAP follows a sigma coordinate system, which is problematic for our purposes as the vertical levels are not uniformly spaced
  - We divide the vertical dimension into 2000-feet intervals over 22 levels, up to 42,000 feet


reference point rp


grid cube gc
reference point $rp = ref(gc)$


raw trajectory Trj


aligned trajectory $\overline{Trj}$

Weather Concepts

- *Definition 3.4.* A **weather vector** $wv_{dy,hr,gc}$, describing the weather condition in a particular grid cube gc at a particular hour hr of a day dy, consists of 4 weather parameters, namely specific humidity $sh_{dy,hr,gc}$, temperature (Kelvins) $tk_{dy,hr,gc}$, wind speed $ws_{dy,hr,gc}$ and wind direction $wd_{dy,hr,gc}$,

$$wv_{dy,hr,gc} = \begin{bmatrix} sh_{dy,hr,gc} \\ tk_{dy,hr,gc} \\ ws_{dy,hr,gc} \\ wd_{dy,hr,gc} \end{bmatrix}$$

- Given a timestamp ts, we also write $wv_{ts,gc}$ as a shortcut for $wv_{date(ts),hour(ts),gc}$

Weather Binning Concepts

- We map each continuous weather vector wv to a discrete bin vector $wb = bin(wv)$, based on a set of intervals that is specific to each grid cube gc:
  - Wind direction is divided using the four cardinal directions
  - Other parameters are split at the first standard deviation

Bin intervals for *sh* (same calculations apply for *tk* and *ws*)	
Bin no.	Interval
1	$(\mu_{sh,gc} - \sigma_{sh,gc}) < sh < (\mu_{sh,gc} + \sigma_{sh,gc})$
2	$sh > (\mu_{sh,gc} + \sigma_{sh,gc})$
3	$sh < (\mu_{sh,gc} - \sigma_{sh,gc})$

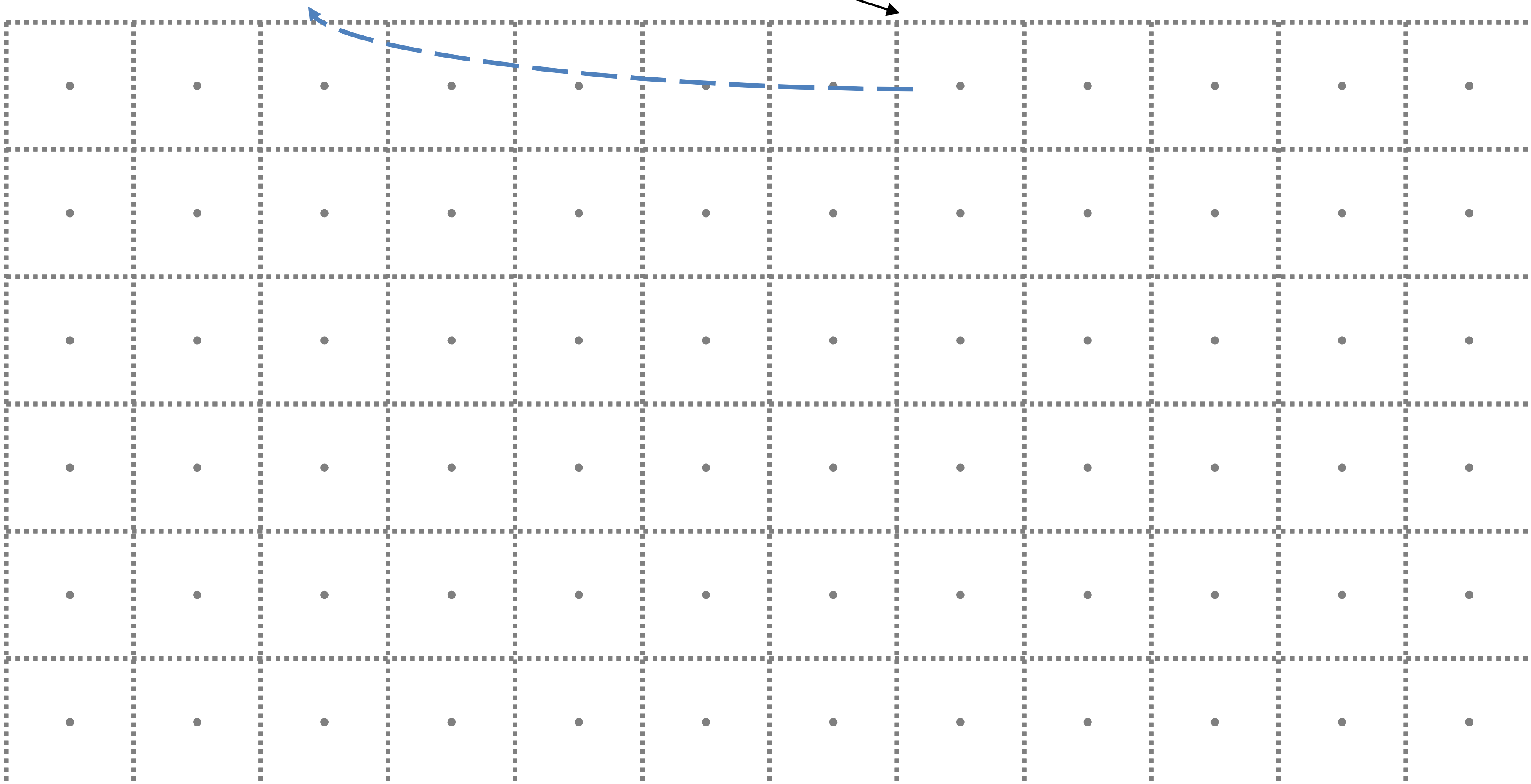
Bin intervals for *wd*	
Bin no.	Interval
1	$315(= -45) < wd < 45$
2	$45 < wd < 135$
3	$135 < wd < 225$
4	$225 < wd < 315(= -45)$

G: the set of all grid cubes

W: the set of all possible bin vectors

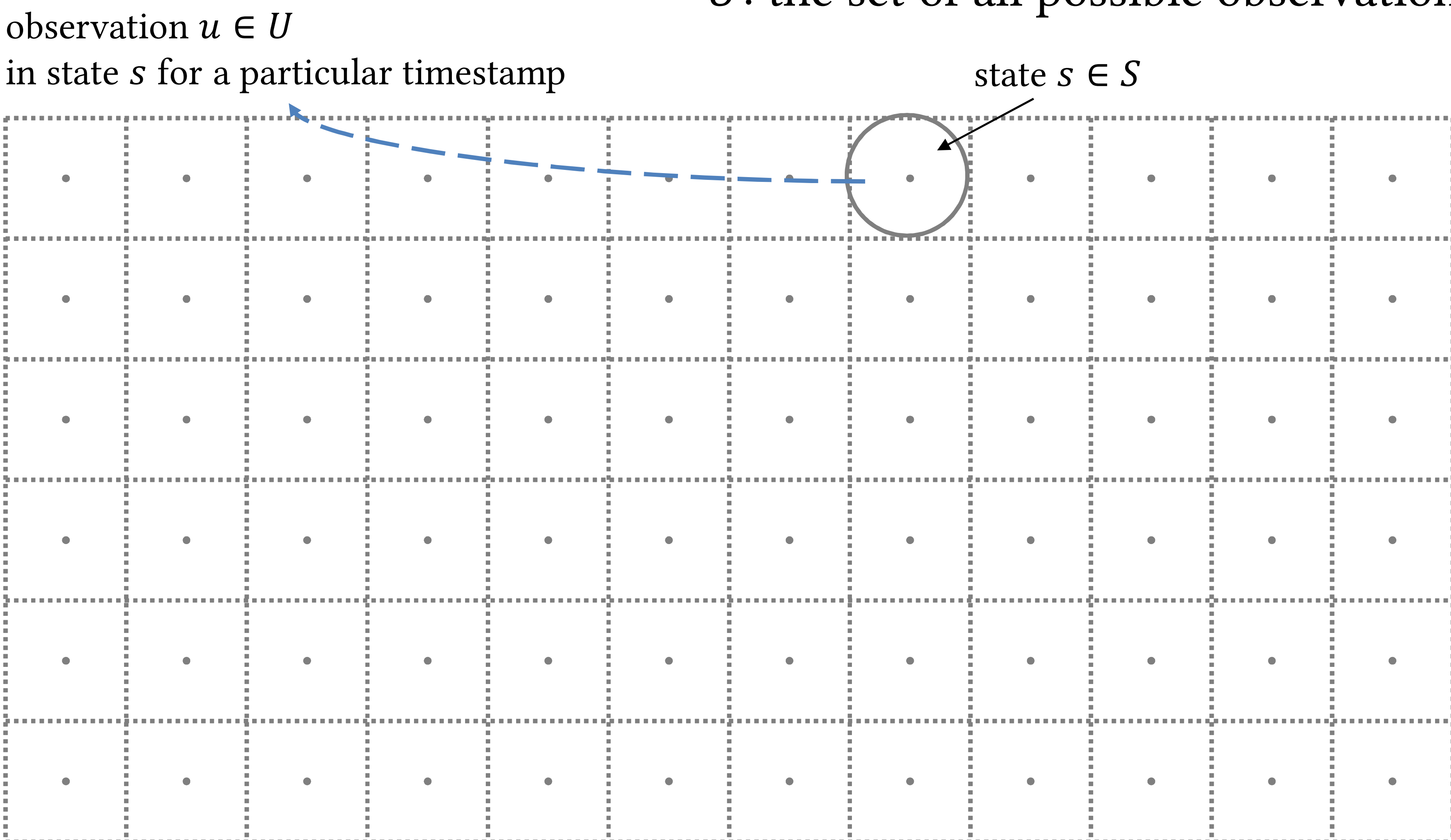
bin vector $bin(wv) = wb \in W$
in grid cube gc for a particular hour

grid cube $gc \in G$



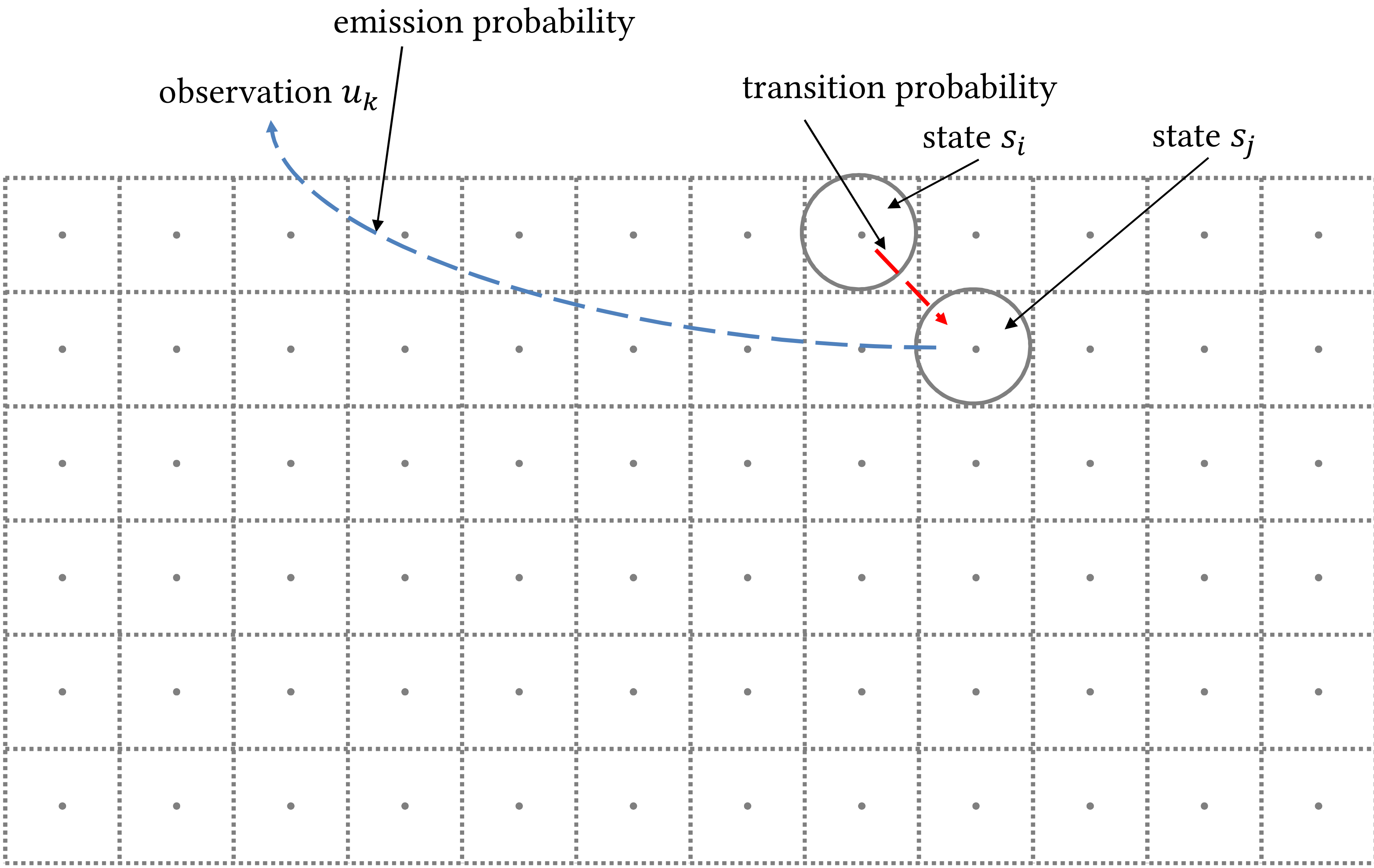
S: the set of all hidden states

U: the set of all possible observations



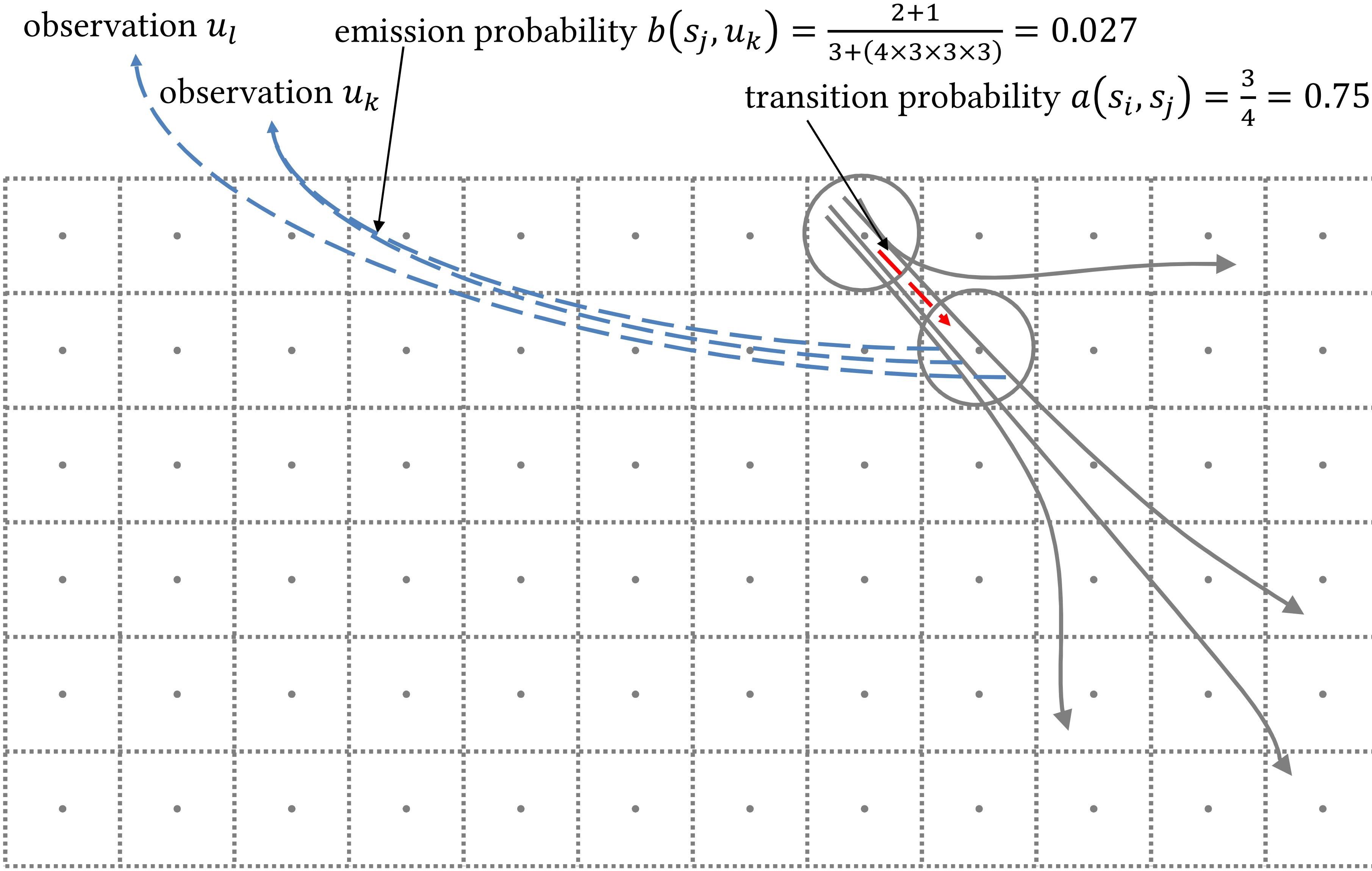
Transition/Emission Probabilities

- Transition probability $a(s_i, s_j)$: probability of an aircraft moving from grid cube gc_i (i.e. from state s_i) to grid cube gc_j (i.e. to state s_j)
- Emission probability $b(s_j, u_k)$: probability of an aircraft experiencing a weather wb_k (i.e. observation u_k), when the aircraft is in grid cube gc_j (i.e. in state s_j)


emission probability
observation u_k
transition probability
state s_i
state s_j

Estimating Probabilities

- Transition probability $a(s_i, s_j)$: counting occurrences
- Emission probability $b(s_j, u_k)$: counting occurrences, with Laplace Smoothing by adding a pseudo-count of 1 for each possible observation (i.e. “Add-One Smoothing”)

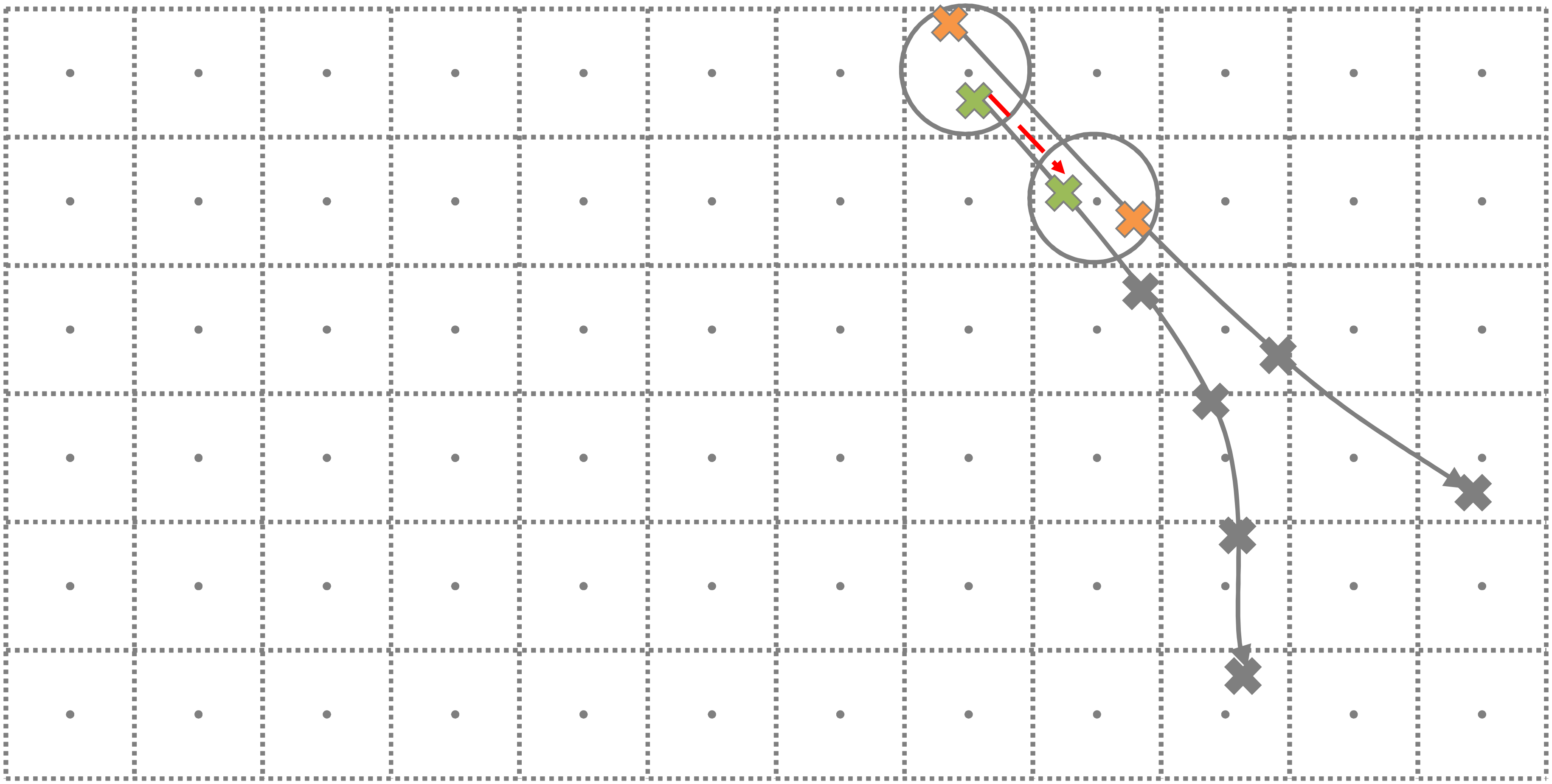


observation u_l
observation u_k
emission probability $b(s_j, u_k) = \frac{2+1}{3+(4\times3\times3\times3)} = 0.027$
transition probability $a(s_i, s_j) = \frac{3}{4} = 0.75$

Using a single prediction model

- Inherent limitation of HMMs: no explicit representation of time duration in each state
- In a first approach, we trained a model based on 1-minute state transitions, then applied the Viterbi algorithm to find the most likely state sequence of length L, representing the predicted trajectory for the next L minutes
- Predictions had big errors for large values of L (e.g. $L = 15$), due to the extra error introduced during discretization having accumulated over L transitions

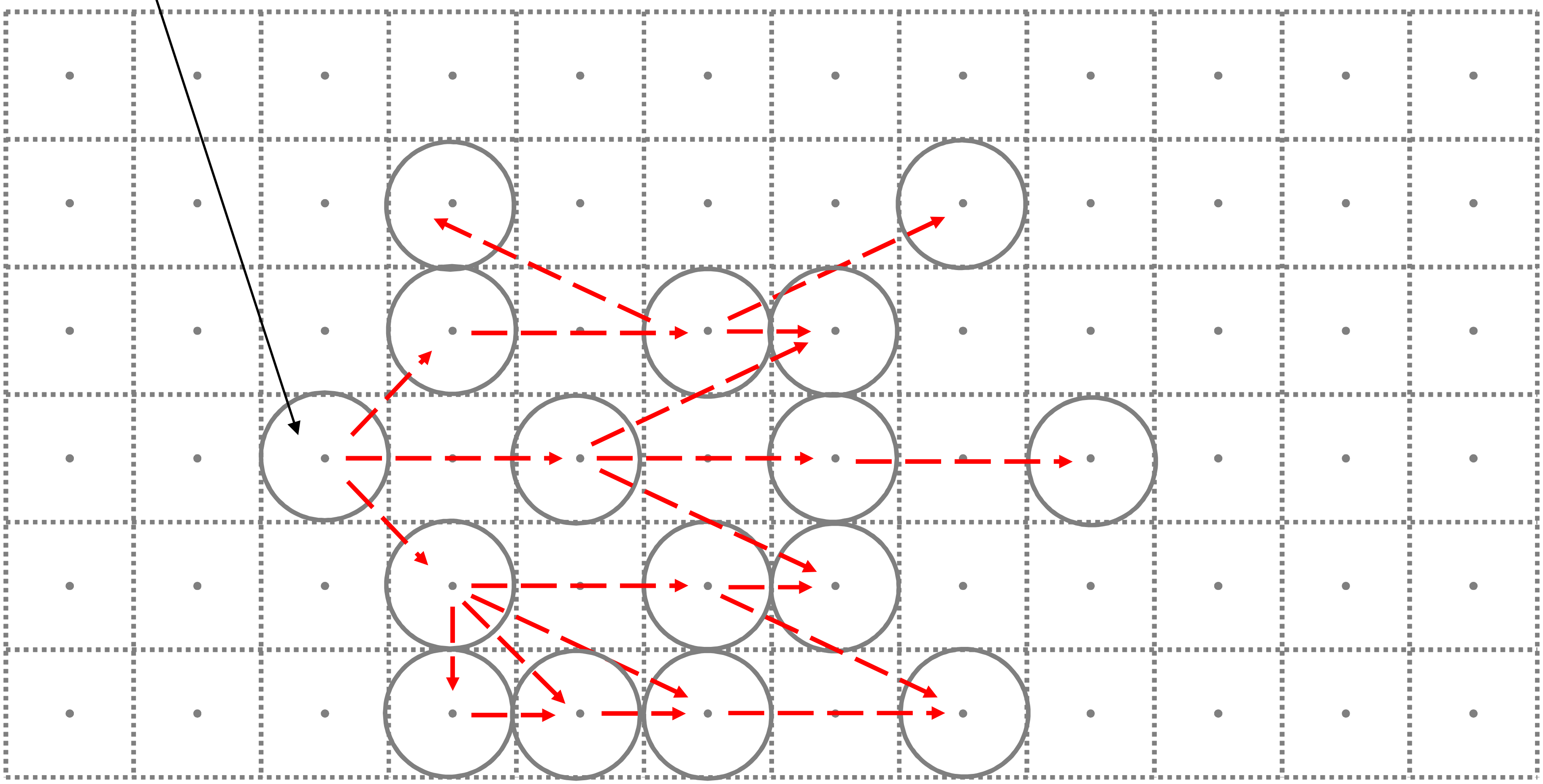
Error introduced during discretization:
both orange positions and green positions
contribute to counting the same transition probability
despite different distances travelled (almost double!)



observations are omitted from this diagram

start state $q_{ts_{now}} \in S$ corresponds to current position of aircraft

Example of a state transition graph (probability values are omitted)



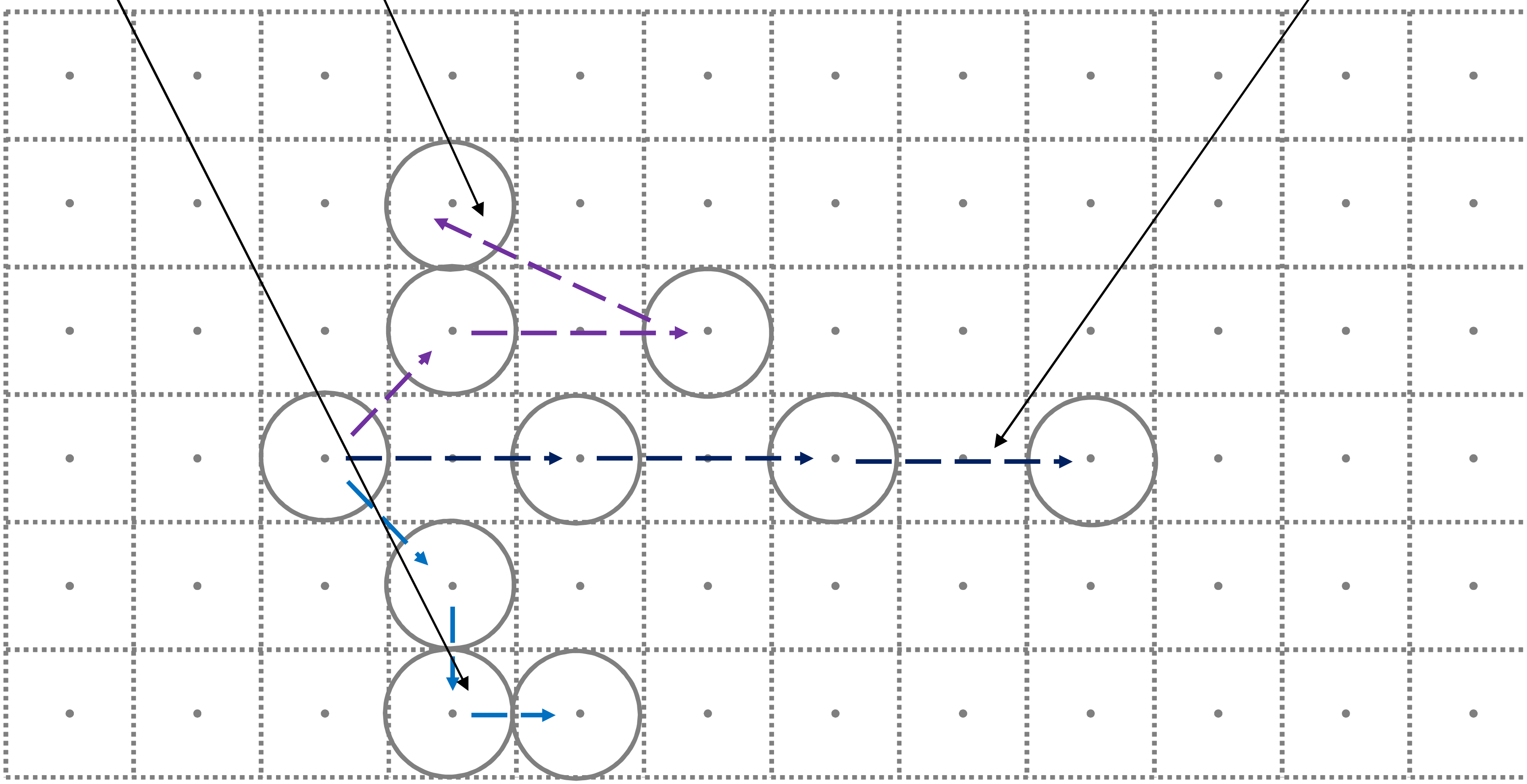
defies Physics

Some trajectories don't make sense;
the Markov Assumption (i.e. memoryless property) violates the Physics of trajectories

observations are omitted from this diagram

might be too short

might be too long

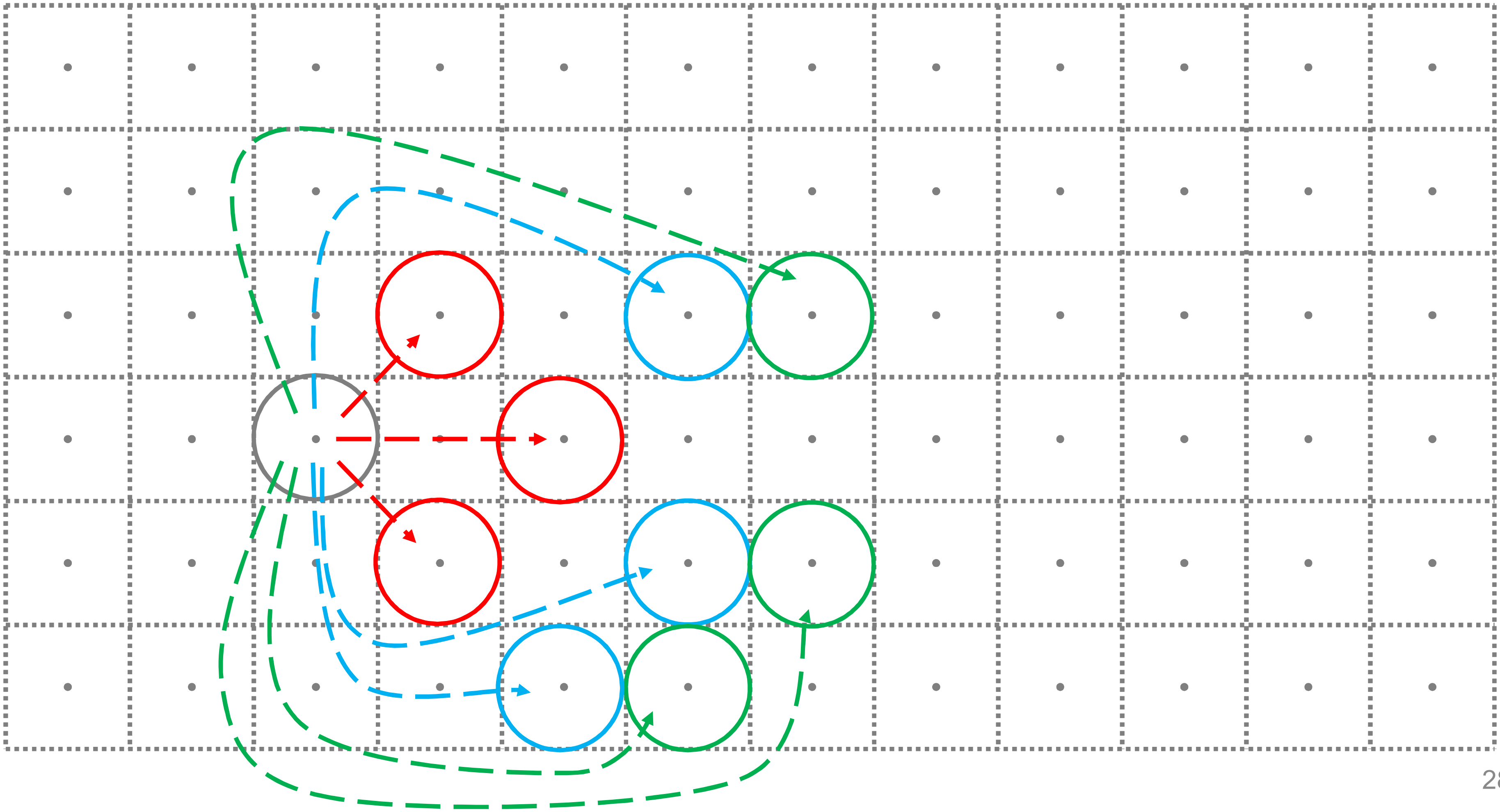


Using multiple models

- Instead of training a single model based on 1-minute transitions, we **train *L* models**, $\mathcal{M}_1, \dots, \mathcal{M}_L$
- Model $\mathcal{M}_t$, $t = 1, \dots, L$, is trained to capture transition probabilities $a(s_i, s_j)$ that an aircraft moves from grid cube gc_i, corresponding to s_i, to grid cube gc_j, corresponding to s_j, **after $\boldsymbol{t}$ minutes**
- We can then use these models to make a prediction for each of the $1, \dots, L$ minutes into the future based on a single state transition

observations are omitted from this diagram

By using a model for each minute, we can ensure that there is no over-estimation or under-estimation



Data Description

- We used trajectory (OpenSky Network) and weather (RAP) data over a period of 25 months (~2 years), from 2017-Jan to 2019-Jan (inclusive)
  - First year (2017-Jan to 2018-Jan) for training
  - Second year (2018-Feb to 2019-Jan) for testing
  - LGA: LaGuardia Airport
  - ORD: Chicago O'Hare Airport
  - BOS: Boston Logan Airport

Route code	Origin / Destination	Mean flight time (minutes)	Number of trajectories	Number of positions
R1	LGA-ORD	116	8036	917299
R2	ORD-LGA	97	4020	389777
R3	BOS-ORD	133	2876	379938
R4	ORD-BOS	108	2049	221820

Baseline Models

We used two baseline models for comparison:

- Kinematics-Based Model (KBM)
  - Projects the current position of the aircraft t minutes into the future based on current track angle, ground speed and vertical rate of the aircraft
- Median Trajectory Model (MTM)
  - Inspired by Ayhan & Samet (2016)'s work on a *pre*-flight application
  - Finds a median trajectory that has the minimum sum of DTW distances to all other trajectories in the training set
  - Finds a position on the median trajectory that is nearest to the current position, and then selecting the position on the median trajectory that is t minutes after

Model Training

We aim to capture seasonal differences in weather patterns

- For each month in the second year (e.g. 2018-Jun), we train a prediction model using the same month in the previous year and its neighbouring months (e.g. 2017-May, 2017-Jun, & 2017-Jul)
- HMM is unable to make predictions for some positions that fall into a grid cube with zero outgoing transition probabilities; in such cases (less than 5% of test data) we fall back on the KBM model to make predictions

Model code	Name of model	Training approach
KBM	Kinematics-Based Model	Training data not required
MTM	Median Trajectory Model	3 months in previous year
HMM	Hidden Markov Model	3 months in previous year

Accuracy Metrics

We used metrics presented by Paglione & Oaks (2007) to measure prediction accuracy

- Horizontal error (always positive): distance along the horizontal plane (latitude-longitude) between predicted and actual positions
- Vertical error (signed): difference in pressure altitude between predicted and actual positions
- When calculating statistics, only the absolute value of vertical error is considered

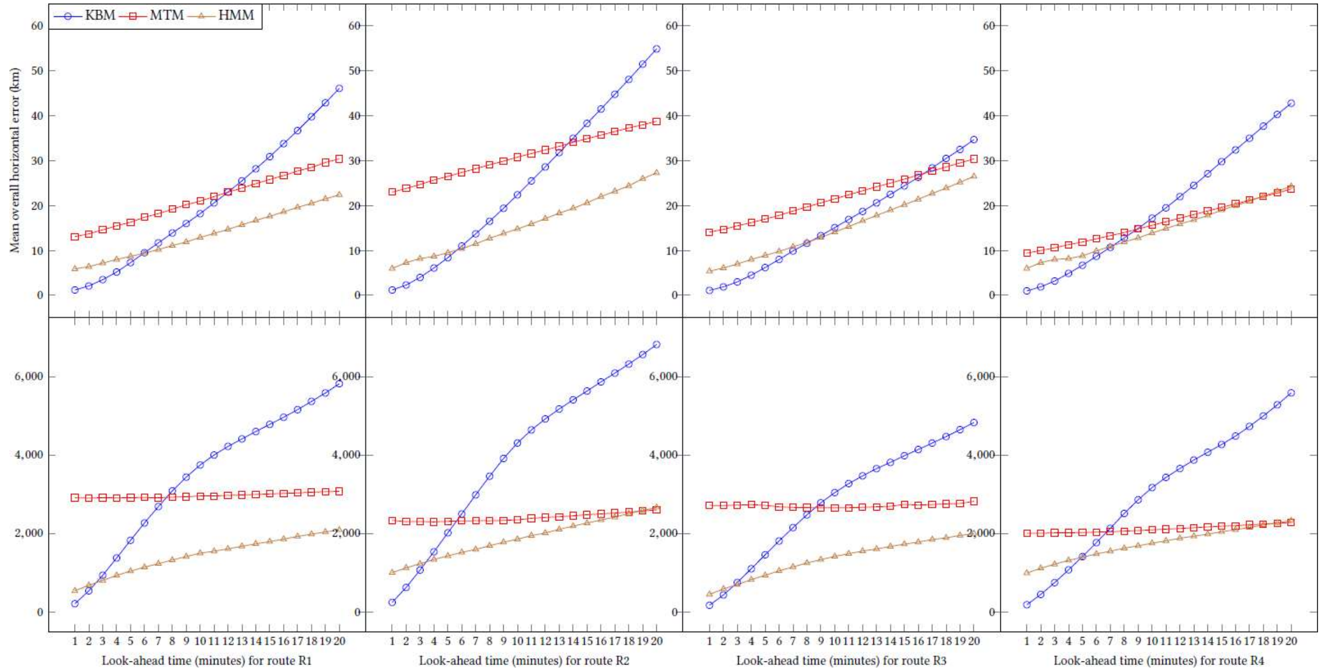
Prediction Time

We computed the average time each model takes for predicting a trajectory of 20 minutes into the future

- Mean of all prediction times taken by the model for all 4 flight routes and all 12 months of test data
- HMM: 39.8 milliseconds
- KBM: 36.9 milliseconds
- MTM: 40.4 milliseconds
- The HMM approach was able to make predictions as efficiently as the baseline models

Prediction Accuracy

- KBM is most accurate for short look-ahead times
- MTM has inconsistent performance (i.e. larger standard deviations)
- HMM outperforms, in general, the baseline models significantly
- Performance of HMM will improve as more data becomes available



Future Work

- More in-depth studies of the effect of incorporating weather and or other information in trajectory prediction
- Experiments on more varied flight routes, and exploration of other ways of incorporating such information
- Use of more complex models, such as higher-order Markov Models

Acknowledgements

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