



Unsupervised Plan Detection In Maritime GPS Data

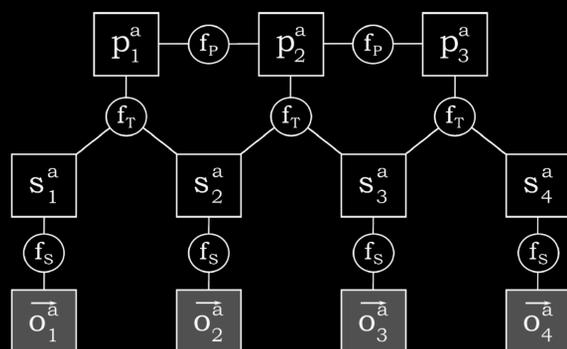


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Plan Detection with Factor Graphs Automating Traffic Monitoring

- Human analysts can look at maps and traces and guess ship destinations, but there are too many to check all!
- We automate plan detection by assuming that ships have hidden plans (destinations) that influence their actions.
- The relationship between observed positions and hidden plans is encoded by a probabilistic factor graph
- The graph compactly represents a joint PDF as the product of the following factors measured on the graph variables:



- O variables are GPS locations and speeds at each time step. These observed variables are used to infer the rest.
- S variables are hidden state variables represent a meaningful location and speed.
- P variables are plan variables representing a destination.
- F_S factors measure compatibility between an observation and a Gaussian centered at the state location.
- F_T factors measure the likelihood of transitioning from one location to another, mediated by the current plan.
- F_P factors represent the chance of transitioning to a new plan (which gives a time scale to the network)
- Once model is trained, future locations can be inferred by adding hidden states and performing Gibbs sampling.

Unsupervised Training Dealing with Unlabeled Information

- Factor graphs are typically trained by having a set of data for which hidden values are known.
- Since no such training set exists for MMV data, we must do unsupervised learning: we find a set of assignments to hidden variables and values for factor parameters that has *maximum self-consistency*.
- 2 Variants: Synchronous and Asynchronous EM

Algorithm 1 ASYNCHRONOUS

```

 $w^0 \leftarrow$  Draws from prior
 $\bar{x}^0 \leftarrow$  Random allocation
 $t \leftarrow 1$ 
loop
   $\bar{w}^t \leftarrow \bar{w}^{t-1}$ 
   $\bar{x}^t \leftarrow \bar{x}^{t-1}$ 
  for all  $x \in X$  do
     $\hat{x}^t \leftarrow (x, \arg\max_c P_{\bar{w}^t}(X = x^t \leftarrow (x^t, c)))$ 
     $\bar{w}^t \leftarrow \arg\max_{\bar{w}} P_{\bar{w}}(X = \hat{x}^t)$  (local updates)
  end for
   $t \leftarrow t + 1$ 
end loop

```

Algorithm 2 SYNCHRONOUS

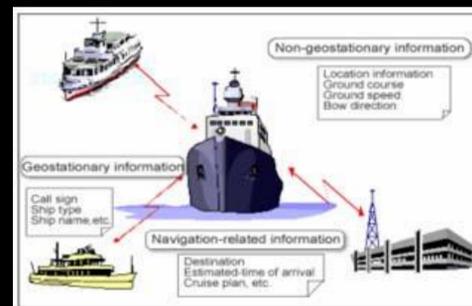
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 $w^0 \leftarrow$  Draws from prior
 $t \leftarrow 0$ 
loop
   $\bar{x}^t \leftarrow \text{MLE}_{\bar{w}}(\bar{x})$  (calls MLBP)
   $\bar{w}^{t+1} \leftarrow \arg\max_{\bar{w}} P_{\bar{w}}(X = \bar{x}^t)$ 
   $t \leftarrow t + 1$ 
end loop

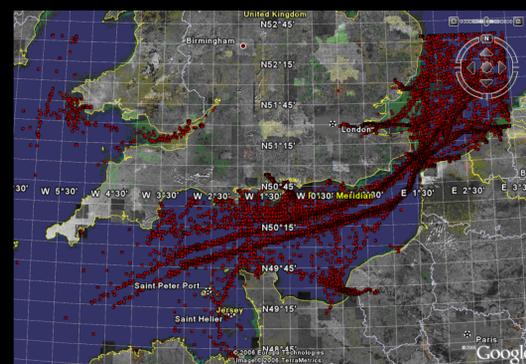
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GPS Data on Merchant Marines Automated Information System (AIS)

- For traffic control and security, large vessels are required internationally to carry an AIS transponder
- AIS transponders can be queried from other ships or ground for GPS location, course, and identity



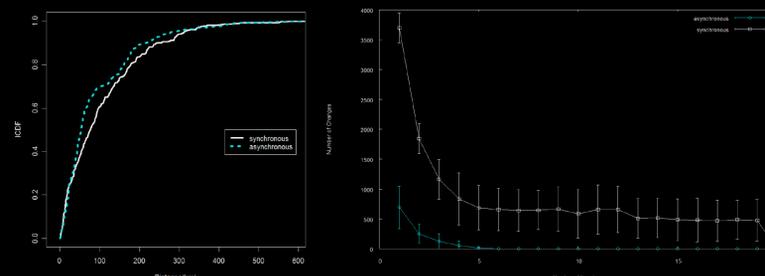
- Sensors queried AIS transponders on vessels traveling through the English Channel over a period of 5 days.
- Over 40000 observations of over 1700 ships were recorded. A small sample is visualized below.



Initial Results

Coarse but Promising Predictions

- Asynchronous updates outperformed Synchronous updates in terms of both convergence rate and prediction accuracy.



- Learned map of likely transitions was compelling but coarse – future work must improve map resolution.

