

#### A Location Predictor based on Dependencies Between Multiple Lifelog Data

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## **Location Prediction**



By predicting future locations, we can provide useful information to a user.



- Time limited sale info at the supermarkets near the predicted locations
- Weather info of future locations
- •To-Do Tasks related to future locations



## **Related Works**

#### Extract and use regularities in movement

### from location log

- Markov Model[Ashbrook, 2003]
- •Dynamic Bayesian Network[Liao, 2007]
- Sequential Pattern Mining[Monreale, 2009]



### Problems



Since previous research uses regularities, they cannot predict irregular movements.

### Regular

go to school on weekdays go to the gym every Monday etc...

#### Irregular

irregular meeting business trips etc...



### Our proposal

Integrate different kinds of lifelogs to predict both regular and irregular movements

#### Regular

go to school on weekdays go to the gym every Monday. etc...

### Irregular

irregular meeting business trips

can predict with location log.

can predict with integrating different kinds of logs.





# We use calendar data as a source for making predictions of irregular movements



- People enter info about irregular events into it
- Widely used.

### Dynamic Bayesian Networks modelNTT () for integrating different data.

DBN model can make reasonable predictions when prediction with only calendar/GPS data is difficult





### Preprocesses





#### Simple model for predicting locations. Can predict regular movements.



Can predict irregular movements

## DBN model (basic)



### Integrate place-place relationship and place-keyword relationship



## DBN model (actual model)

Make some extensions to basic model.

- add node that represents time of day, stay duration





## Learning

- Estimating the parameters of the probability distributions of DBN from data.
- Using maximum a posteriori (MAP) estimation.

### Inference



Use the Viterbi algorithm to infer a state sequence that maximizes probability.





### **Experimental Settings**

Whether prediction accuracy is improved or not by using calendar data.

Baseline:

DBN model without Calendar data

Dataset

GPS and calendar data of two subject

(about 50 days)

Table 1: Information about data set.		
	Subject A	Subject B
# of days	48	54
# of clusters	118	79
# of calendar entries	66	149
# of stays	827	432

## **Evaluation metrics**



 Evaluate the accuracy of prediction by changing the time difference between the subject of prediction and the time to start prediction





## **Prediction Results**

#### **Regular Movements**

#### Subject A



Subject B

There are no much differences.

### **Prediction Results**



#### **Irregular Movements**

#### Subject A

Cop



Subject B

The accuracy was improved for irregular movements

### **Example of Predictions**





(a) The use of calendar data yields wrong predictions

The prediction failed since the wrong place is estimated from the calendar entry



### **Example of Predictions**



(b) The modified predictions

The result was modified because the time needed for movement was considered



### Conclusion

- We show a DBN model for making prediction for both regular and irregular movements by using GPS and calendar data.
  - The accuracy of predictions for irregular movement was improved.
  - Wrong prediction due to wrong schedule can be modified by using GPS data.

- Future works
  - Use other kinds of logs.

### Thank you.

