Ubiquitous and Mobile Computing

CS 528: My Smartphone Knows I am Hungry

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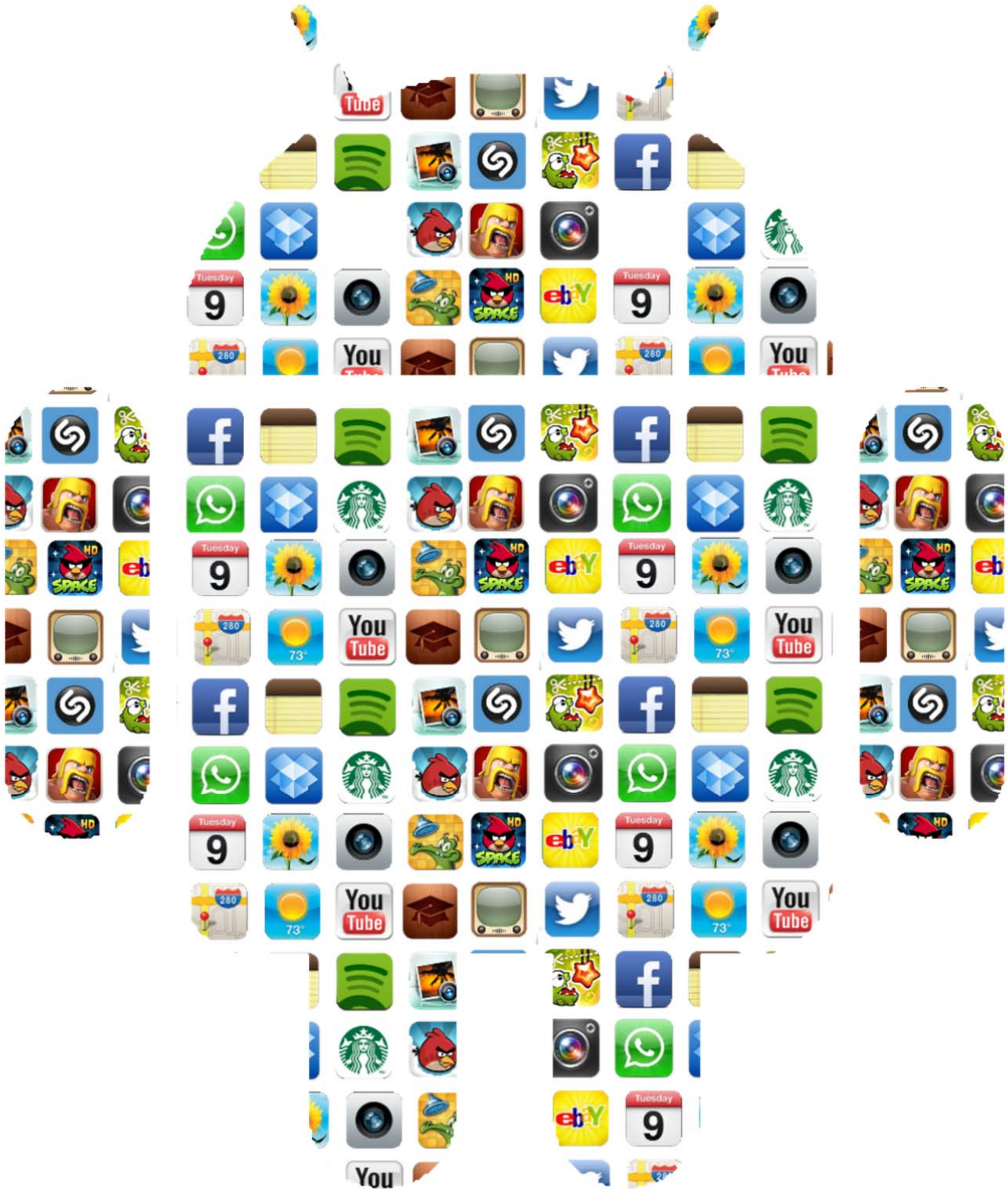
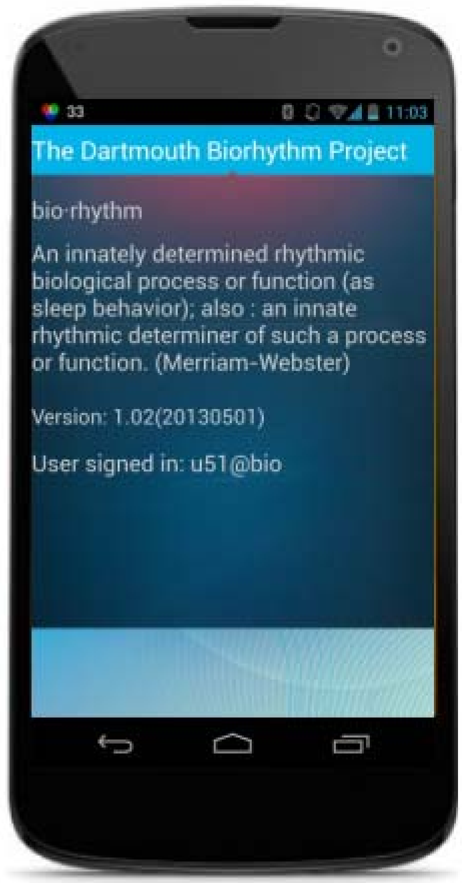
Smartphone and Unhealthy Eating


LG





- 25 Students
- 10 weeks
- Run in background 24/7
- Collect:
  - Conversation
  - Physical activity
  - Sleep
  - Location
  - Wifi scan log & Bluetooth colocation

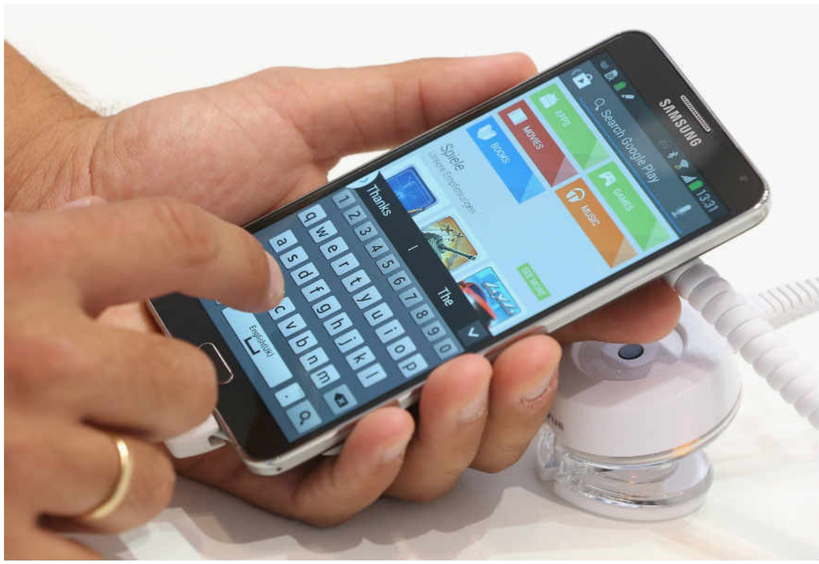

TO-DOLIST
NOTHING

Result

- After 3 week training data, we can predict food purchases with accuracy

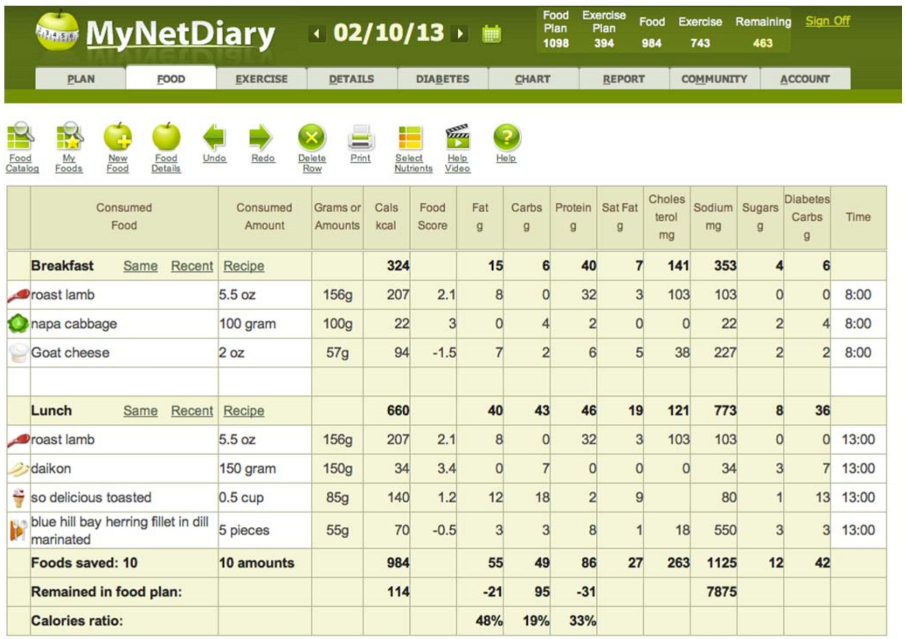
74%

Other related researches



Differences

Differences



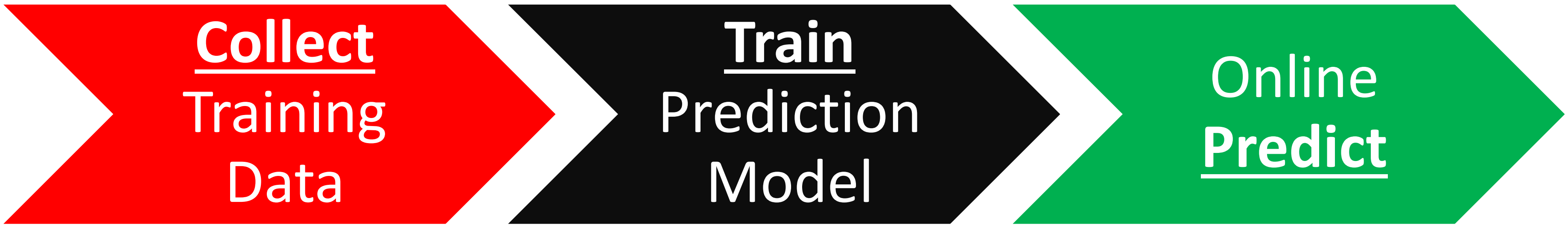
Consumed Food	Consumed Amount	Grams or Amounts	Cals kcal	Food Score	Fat g	Carbs g	Protein g	Sat Fat g	Cholesterol mg	Sodium mg	Sugars g	Diabetes Carbs g	Time
Breakfast Same Recent	Recipe		**324**		**15**	**6**	**40**	**7**	**141**	**353**	**4**	**6**	
roast lamb	5.5 oz	156g	207	2.1	8	0	32	3	103	103	0	0	8:00
napa cabbage	100 gram	100g	22	3	0	4	2	0	0	22	2	4	8:00
Goat cheese	2 oz	57g	94	-1.5	7	2	6	5	38	227	2	2	8:00
Lunch Same Recent	Recipe		**660**		**40**	**43**	**46**	**19**	**121**	**773**	**8**	**36**	
roast lamb	5.5 oz	156g	207	2.1	8	0	32	3	103	103	0	0	13:00
daikon	150 gram	150g	34	3.4	0	7	0	0	0	34	3	7	13:00
so delicious toasted	0.5 cup	85g	140	1.2	12	18	2	9		80	1	13	13:00
blue hill bay herring fillet in dill marinated	5 pieces	55g	70	-0.5	3	3	8	1	18	550	3	3	13:00
Foods saved: 10	**10 amounts**		**984**		**55**	**49**	**86**	**27**	**263**	**1125**	**12**	**42**	
Remained in food plan:			**114**		**-21**	**95**	**-31**			**7875**			
Calories ratio:					**48%**	**19%**	**33%**						

Simple binary classification problem

Buying

NOT Buying

Methodology



Collect Data Training

Features

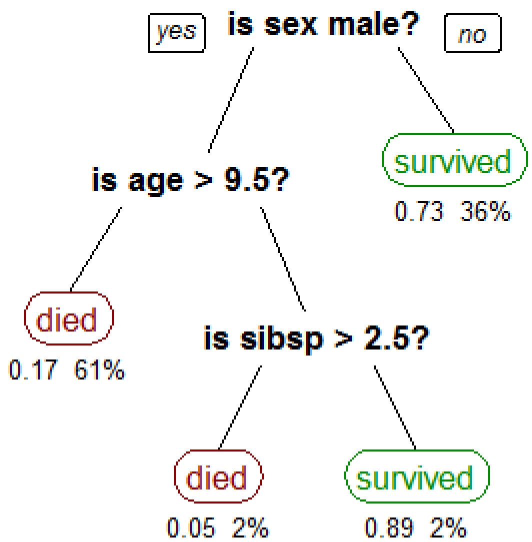
< PREV | Curr >

+ Physical activity
+ Sociability

+ Current building
+ Arrival time

Why?

Train Prediction Model



Classification and Regression Tree (CART)

$$I_G(f) = \sum_{i=1}^{m} f_i(1 - f_i) = \sum_{i=1}^{m}(f_i - f_i{}^2) = \sum_{i=1}^{m} f_i - \sum_{i=1}^{m} f_i{}^2 = 1 - \sum_{i=1}^{m} f_i{}^2$$

Gini impurity

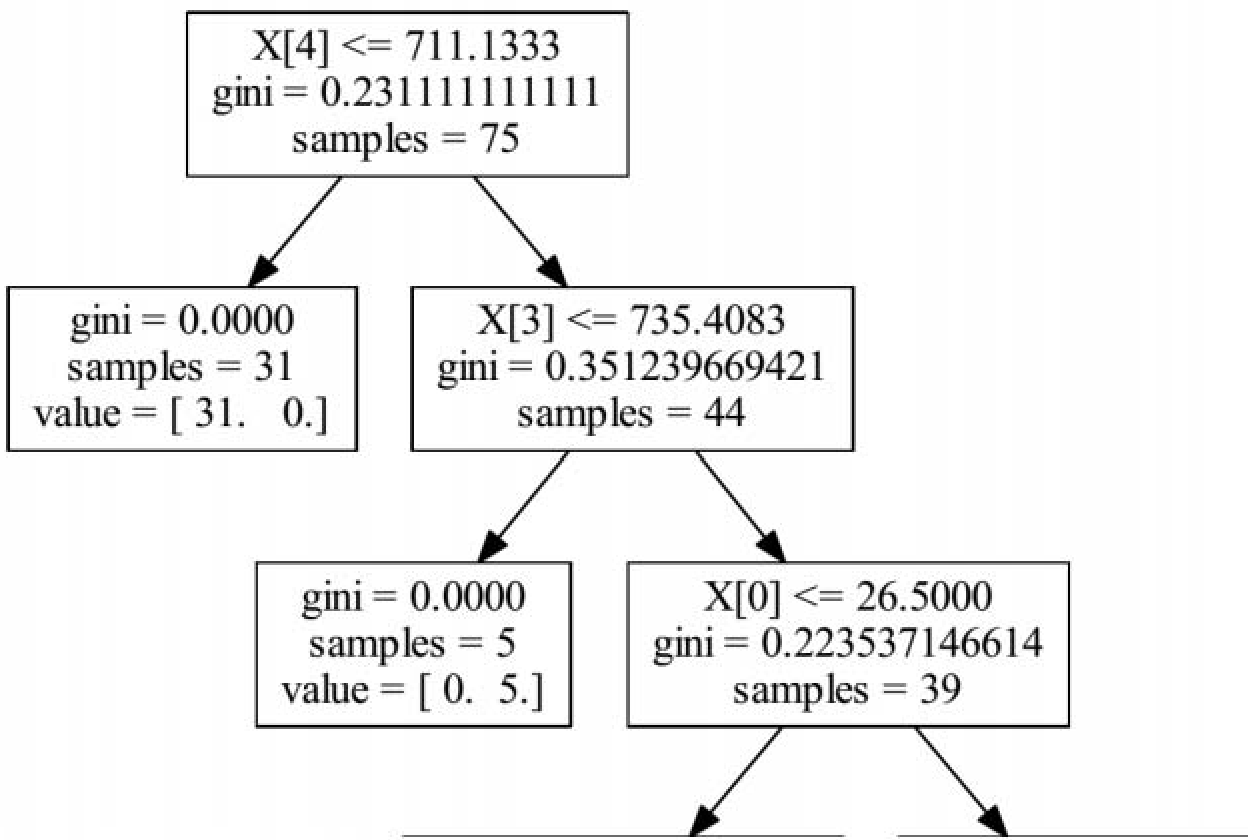
http://en.wikipedia.org/wiki/Decision_tree_learning#Gini_impurity

Predict

Design

- CART + Gini Impurity

Prediction Model and Traversal

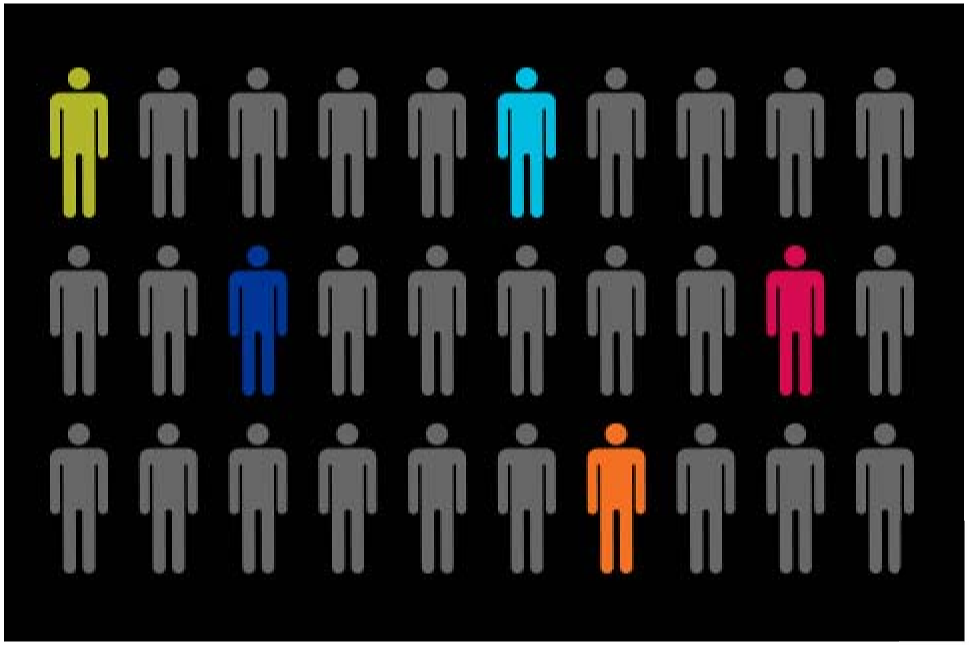


decision tree

Can we do better?

Implementation Enhancement

- Personalization
- Adaptation

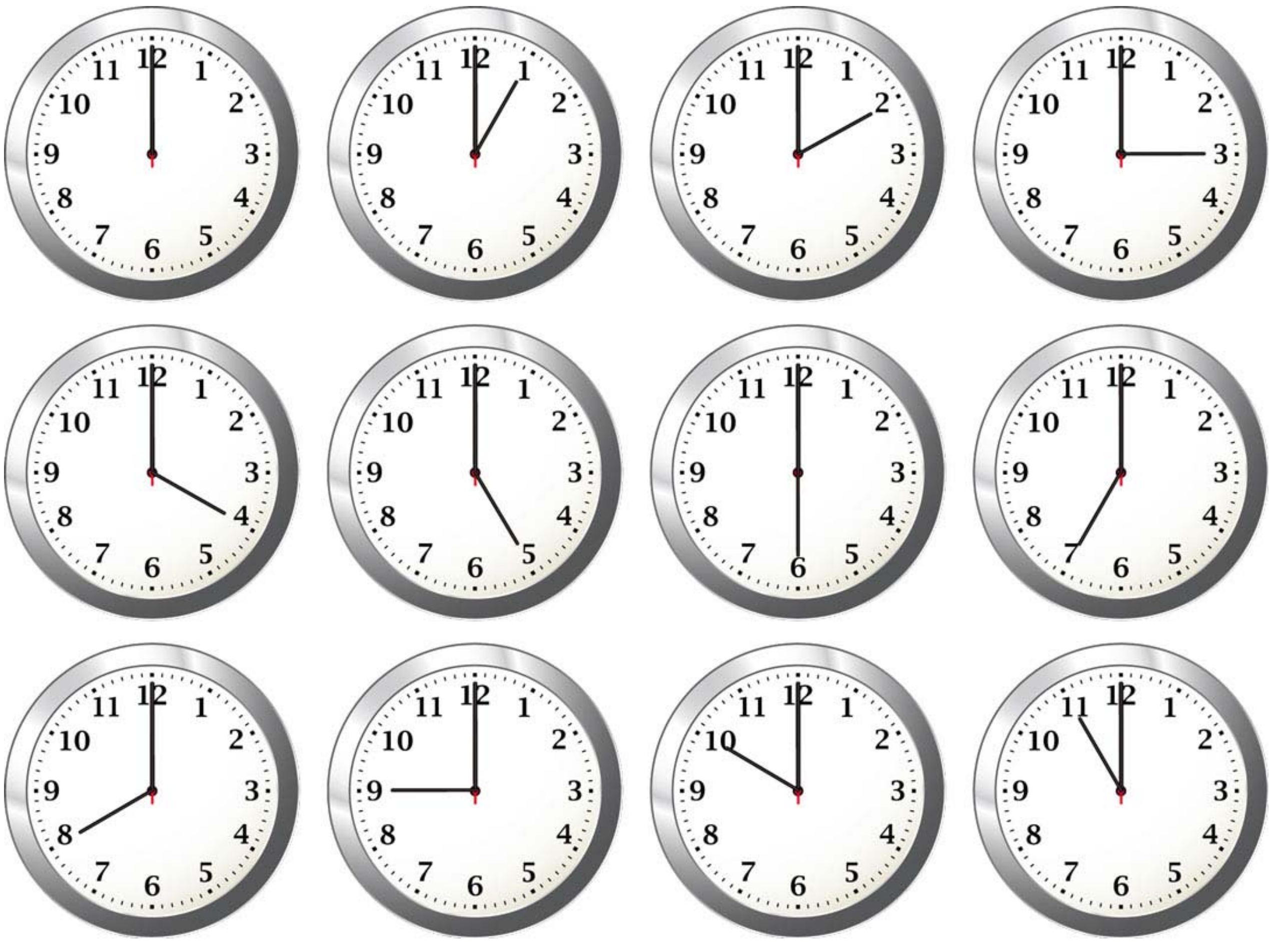


Behaviors
Schedules
Locations

Implementation Enhancement

- Personalization
- **Adaptation**

Eating time in a month



Results

- Importance of different features (top 6)
- Prediction Performance

Results

- **Importance of different features (top 6)**
  - **Current building**
  - **Arrival time at current building**
  - **Departure time from previous building**
  - **Activity ratio in last building**
  - **Departure time from current building**
  - **Conversation duration**
- Prediction Performance

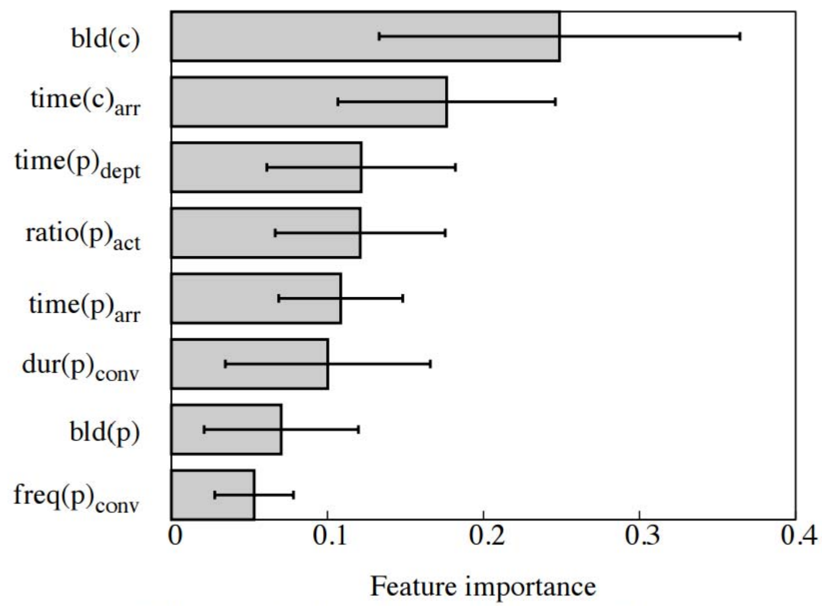
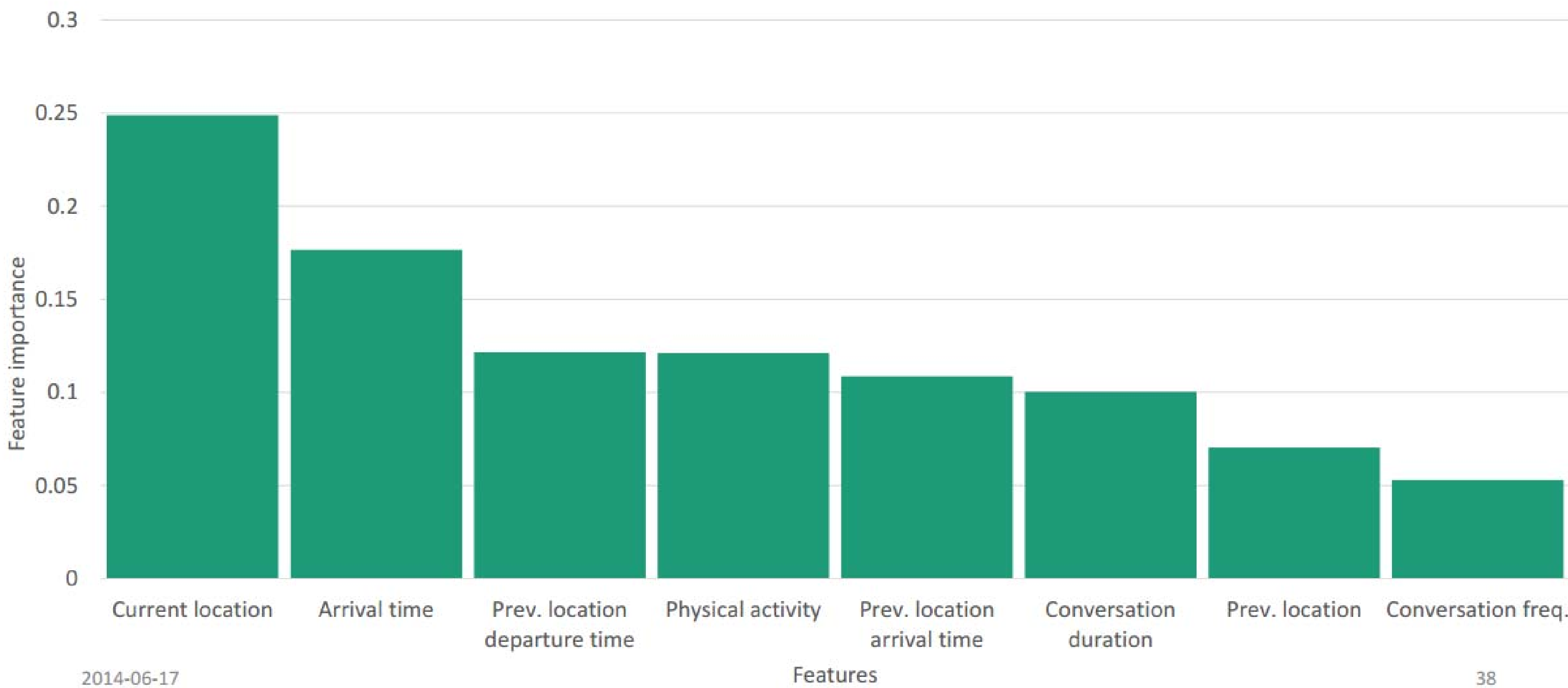


Figure 2: Ranking of feature importance.


0.3
0.25
0.2
0.15
0.1
0.05
0
Feature importance
Current location
Arrival time
Prev. location departure time
Physical activity
Prev. location arrival time
Conversation duration
Prev. location
Conversation freq.
Features

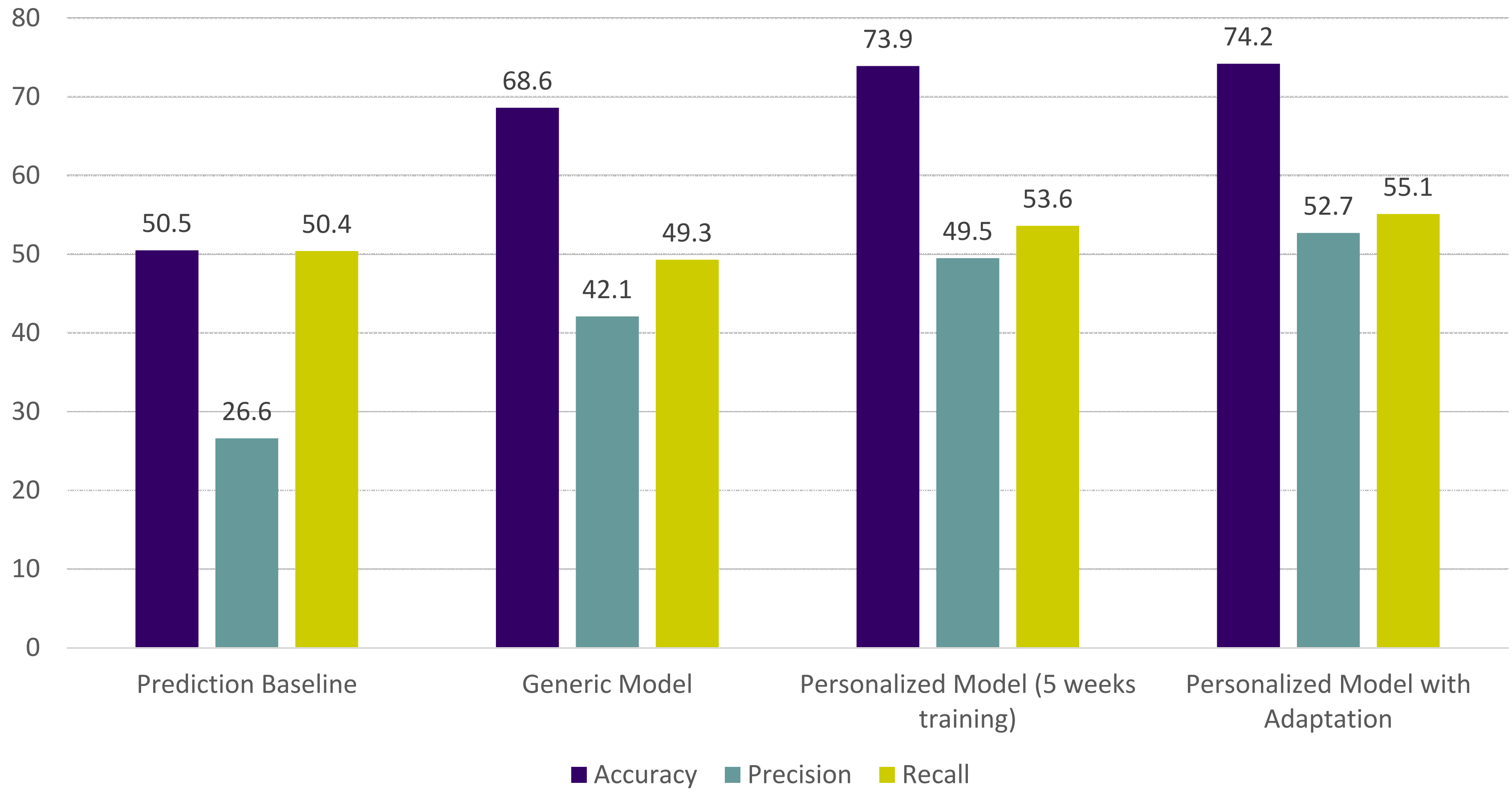
Results

- Importance of different features (top 6)
- **Prediction Performance**

Terminology

- Accuracy measures how well a binary classification test correctly identifies labels
- Precision measures the probability that a test case given positive label is truly positive
- Recall measures the probability that a positive case can be identified by the classifier

Prediction Performance



Personalized Model without Adaptation

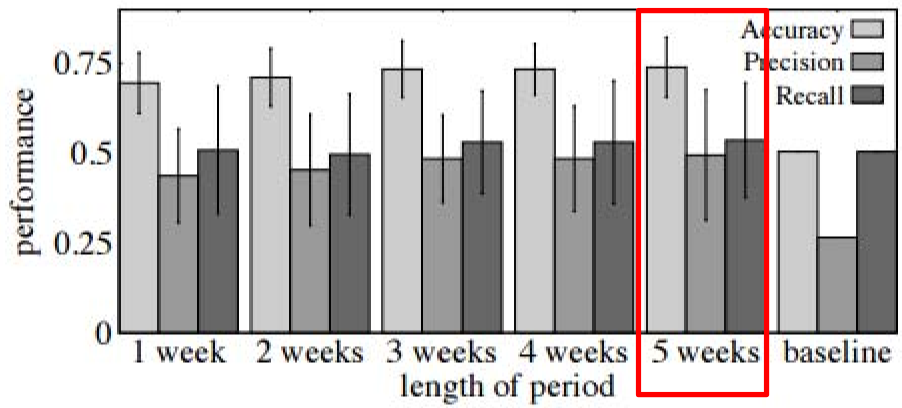


Figure 3: Prediction performance for the static training set.

Personalized Model with Adaptation

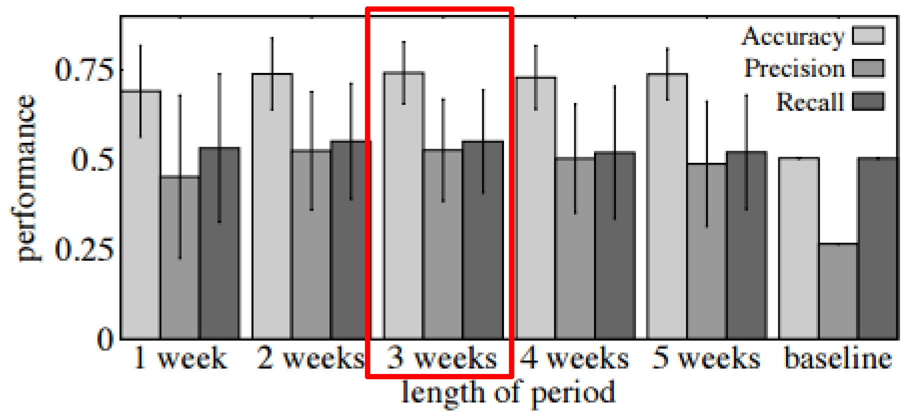


Figure 4: Prediction performance for different adaption periods.

Conclusion

- Feature importance
- Model to predict eating habit

Future Researches

- To generalize the work, explore more features for prediction of more types of food purchases
  - Purchase cost
  - Purchase type
  - Total number of daily purchase instance
- New target users: Office workers
- How to unobtrusively detect eating?
- Food intervention

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