Mobile Sensing: Spring 2015
Exercise: 2
Solutions

Due on 19th March 2015 by 17:45 PM.

Instructions: All course participants are requested to submit their exercise solutions electronically to the instructors (samuli.hemminki at cs.helsinki.fi and teemu.pulkkinen at cs.helsinki.fi), as well as to the course lecturer (petteri.nurmi at cs.helsinki.fi) by the due date (latest before the exercise session). In all the exercises, do not just give the answer, but also the derivation how you obtained it. Participants are encouraged to write computer programs to derive solutions to some of the given problems.

Ex 1. Annotation

1. Consider the annotations given for two users A and B in Table 1. Calculate Cohen's Kappa for the agreement between A and B. Are the measurements reliable? Can they be used for developing sensing algorithms?

   $\mathrm{P(W|A)} = \frac{6+44}{62+44+12+6} = \frac{50}{124}$
   $\mathrm{P(W|B)} = \frac{56}{124}$
   $\mathrm{P(R|A)} = \frac{74}{124}$
   $\mathrm{P(R|B)} = \frac{68}{124}$

   $\mathrm{P(W|\ A\ \&\ B)} = \frac{50*56}{124^2} \approx 0.1821$
   $\mathrm{P(R|\ A\ \&\ B)} = \frac{74*68}{124^2} \approx 0.3273$

   $\mathrm{Pr(e)} = \mathrm{P(W|\ A\ \&\ B)} + \mathrm{P(R|\ A\ \&\ B)} \approx 0.509$

   Agreement: $\frac{62+44}{124} = \frac{106}{124} \approx 0.855$
   $\kappa = \frac{0.855-0.509}{1-0.509} \approx 0.70$
   Reliability? OK, but not great. Could be used for development.

2. Consider the questionnaire answers given in Table 2. Calculate Cronbach's alpha. Are the measurements reliable? Can the measurements be used?
   MATLAB can give us the answer quite easily:

```
quest = [5 2 3 5 4; 4 3 5 4 3; 3 2 4 1 1; 4 3 5 4 2; 3 1 1 2 3];
K = size(quest,2);
cronbach = (K/(K-1))*(1-(sum(var(quest))/var(sum(quest,2))));
%Note that we use the 'dim' parameter in the second sum
%to sum over columns (instead of rows, which is the default).
%Run this and we get:

cronbach =

         0.745073891625616
```

   Since alpha is $\geq$0.70, these measurements are reliable.

3. What happens when the answers of a malicious user (Table 3) are added to the table?

```
quest = quest2 = [5 2 3 5 4; 4 3 5 4 3; 3 2 4 1 1; 4 3 5 4 2; 3 1 1 2 3; 1 2 3 4 5];
K = size(quest2,2);
cronbach = (K/(K-1))*(1-(sum(var(quest2))/var(sum(quest2,2))));
%This gives us

cronbach =

         0.558401639344262
```

   This alpha is below the minimum acceptable value, which means this questionnaire is probably not valid.

A — B	**Running**	**Walking**
Running	62	12
Walking	6	44

Table 1: Annotation

Ex 2. Sensing Evaluation

Consider the two classifier outputs and the ground truth given in Table 4.

a) Score the outputs of the classifiers into TP, FP, FN and, TN for each of the two classes

b) Calculate the precision, recall, and F1-score for both classes (W and S) of the two classifiers

	1	**2**	**3**	**4**	**5**
User 1	5	2	3	5	4
User 2	4	3	5	4	3
User 3	3	2	4	1	1
User 4	4	3	5	4	2
User 5	3	1	1	2	3

Table 2: Questionnaire 1

User 6	1	2	3	4	5

Table 3: Responses from a malicious user

c) Calculate the fragmentation rate of the two classifier (for both classes and classifiers).

Ground truth	**W**	**W**	**W**	**S**	**W**	**S**	**S**	**S**	**S**	**W**
Classifier 1	W	W	W	S	S	W	W	S	S	W
Walking	TP	TP	TP	TN	FN	FP	FP	TN	TN	TP
Standing	TN	TN	TN	TP	FP	FN	FN	TP	TP	TN
Classifier 2	W	S	W	S	S	S	W	S	W	W
Walking	TP	FN	TP	TN	FN	TN	FP	TN	FP	TP
Standing	TN	FP	TN	TP	FP	TP	FN	TP	FN	TN

Precision (W|C1) $= \frac{4}{4+2} = \frac{2}{3} \approx 67\%$
Recall (W|C1) $= \frac{4}{4+1} = \frac{4}{5} = 80\%$
F1 (W|C1) $= \frac{2*4}{2*4+2+1} = \frac{8}{11} \approx 73\%$
(alternatively: $2 \cdot \frac{\frac{2}{3} \cdot \frac{4}{5}}{\frac{2}{3}+\frac{4}{5}}$)

Precision (S|C1) $= \frac{3}{4} = 75\%$
Recall (S|C1) $= \frac{3}{5} = 60\%$
F1 (S|C1) $= \frac{6}{9} \approx 67\%$

Precision (W|C2) $= \frac{3}{5} = 60\%$
Recall (W|C2) $= \frac{3}{5} = 60\%$
F1 (W|C2) $= \frac{6}{10} = 60\%$

Precision (S|C2) $= \frac{3}{5} = 60\%$
Recall (S|C2) $= \frac{3}{5} = 60\%$
F1 (S|C2) $= \frac{6}{10} \approx 60\%$

Fragmentation: The are 5 events in the ground truth labels (= "true events").

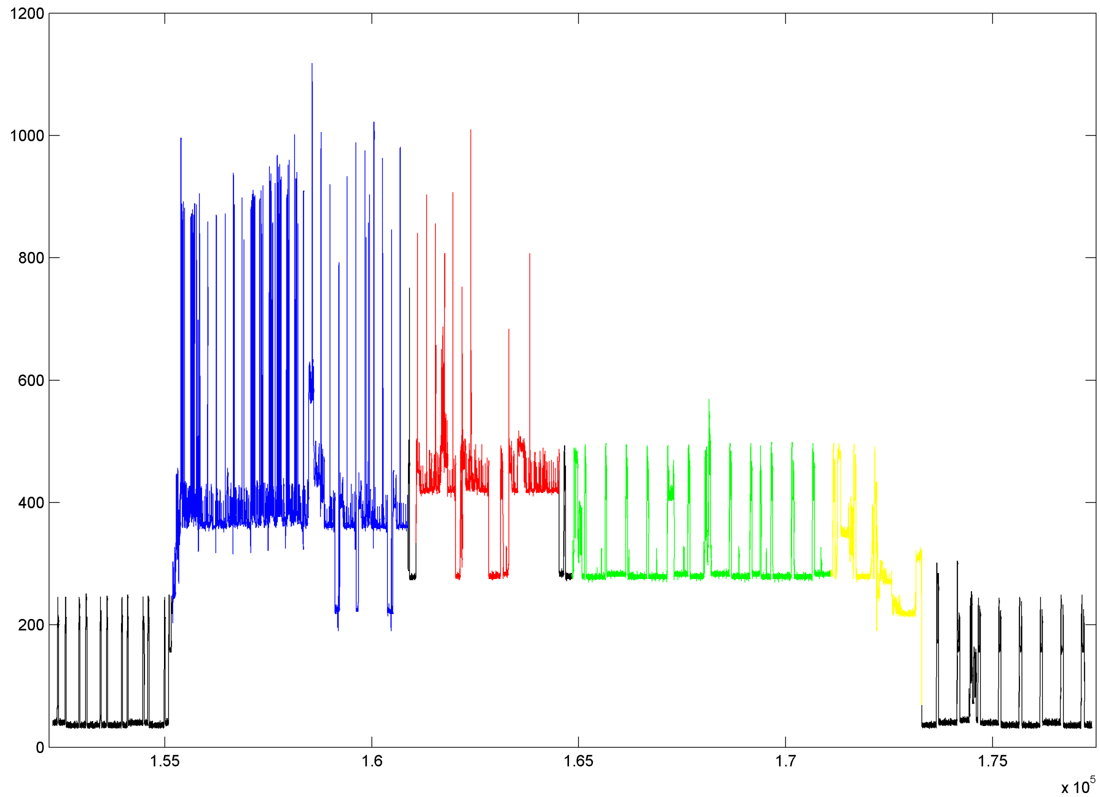
There are two fragmentation errors in the table. They occur with "Classifier 2" in both classes (TP-FN-TP sequence). The fragmentation rate for (W|C2) and (S|C2) is thus $\frac{1}{5} = 20\%$. For all other classes/classifiers it is 0.

Ground truth	**W**	**W**	**W**	**S**	**W**	**S**	**S**	**S**	**S**	**W**
Classifier 1	W	W	W	S	S	W	W	S	S	W
Classifier 2	W	S	W	S	S	S	W	S	W	W

Table 4: Classification

Ex 3. Energy Modelling

a) Consider the measurements shown in Fig. 1. How many different states does the sensor have?
3-4 (up to interpretation, since this is real data).



In the above figure the different states have been colored. The black color is considered background energy, and the yellow section (probably) corresponds to a shutdown sequence. We leave this state out.

b) Given the measurements in file energy.mat [1], calculate the mean value for each state. Note that energy is calculated through $voltage \cdot current$. For the states highlighted above, the means are as follows:

   (a) State 1 (blue) : ≈ 398.66

   (b) State 2 (red) : ≈ 417.36

   (c) State 3 (green): ≈ 303.50

c) Consider the that each state is being active for 5 minutes at a time. How much energy does the application consume in one hour?

   3 states for 5 minutes at a time = 15 minutes, which means we get 4 of these cycles in one hour. The averages we calculated in b) gives us the (average) energy used in one second. Thus, the total energy consumed is 4*5*60*mean(State1) + 4*5*60*mean(State2) + 4*5*60*mean(State3) $\approx$ 1457629.37mJ or $\approx 1458J$.

d) Which sensor you think the data is from? WiFi.

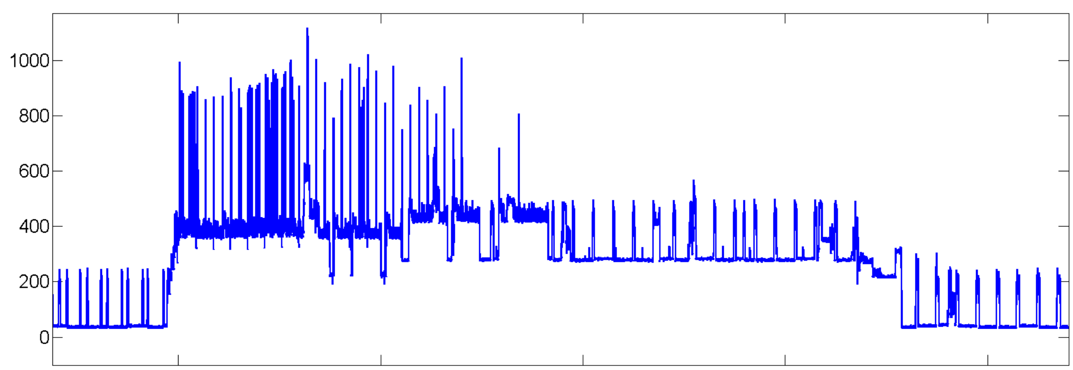


Figure 1: Energy cycle of a single sensor iteration.

[1] In the data, columns 1 to 4 corresponds to: [measurementID, timestamp, voltage, currency]

Ex 4. Sensing Applications
Pick *one* of the following mobile sensing applications: JigSaw, Darwin Phones, UnLoc

Read the corresponding research article and classify the application according to the dimensions given during the lecture (Lec. I). Which sensors are used in these application and what information is extracted from it?

JigSaw: Lu, H.; Yang, J.; Liu, Z.; Lane, N. D.; T., C. & A., C. The Jigsaw continuous sensing engine for mobile phone applications Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems, 2010, 71-84
Darwin Phones: Miluzzo, E.; Cornelius, C. T.; Ramaswamy, A.; Choudhury, T.; Liu, Z. & Campbell, A. T. Darwin Phones: the Evolution of Sensing and Inference on Mobile Phones Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services (MobiSys), ACM, 2010
UnLoc: Wang, H.; Sen, S.; Elgohary, A.; Farid, M.; Youssef, M. & Choudhury, R. R. No need to war-drive: unsupervised indoor localization The 10th International Conference on Mobile Systems, Applications, and Services (MobiSys), ACM, 2012, 197-210

JIGSAW:
Continuous
Personal Sensing
Opportunistic Sensing

Accelerometer: Acceleration, user's activity / transportation mode
Microphone: Audio / Voice classification
GPS: Location, location trajectories
(WiFi: iPhone hybrid localization system)

Other context derived from sensor measurements:
Calories, CO_2

DARWIN PHONES:
** Speaker Recognition **
-On-Demand
-Personal + Community Sensing
-Opportunistic Sensing
Microphone: Audio / Speech
** Virtual Square **
-On-Demand
-Community Sensing
-Opportunistic Sensing

GPS: Location
Magnetometer: Location
** Place Discovery **
-Continuous
-Personal + Community Sensing
-Opportunistic Sensing
WiFi: Location fingerprinting (signal environment)
** Fried Tagging **
-On-Demand
-Opportunistic
No Sensors (Camera)

UnLoc:
Modes: Continuous
Scale: Personal + Community Sensing
(Users are localized individually, but organic landmarks are crowd-sourced.)
Paradigm: Mainly opportunistic, but the user's involvement can be used to map the building entrance.
Sensors: Almost any sensor that can provide a unique (spatially dependent) signature, but mainly:

- WiFi: Fingerprint similarity ("MAC ID, RSSI")
- Magnetometer: Magnetic field strength (anomalies)
- Magnetometer (as compass)+IMU: "mean, max, min, variance, mean-crossings"