Coursework 2

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1. *Describe Mobile Sensing challenges and its applications.*
   Challenges:

   - Sensors are not very accurate. They are general purpose sensors, not specialised, so they have higher level of error. In addition to that position of sensors could vary, we can have different sensors that an application may use on a device (i.e. as in the same app on a device which has sensor X and on another which has sensor Y).
   - Resources are constrained – the app will be:
     - Sharing resources with many other apps – it's running on a mobile device, not a dedicated, where there is an OS which would not dedicate the whole CPU/Memory to a single app.
     - Running on a battery powered device – sensing is resource expensive and drains battery. It also reduces device performance (I have had sensing apps ages ago that made my phone work slower.).
   - There are privacy concerns – sensing could reveal private data about the life of the user (lifestyle, habits, current location, mood, etc.)
   - Given all of the above the app still needs to provide accurate enough data, so that it is still useful – needs to strike a balance between resource usage and accuracy.

   Applications:

   - Monitoring human activity – fitness, health (heart rate, etc), sports, etc
   - Transport-mode detection – contributes to identifying the needs of workers (travelling time, transportation choice, etc.) and supporting creating commuting services to meet the needs
   - Emotion detection
   - Context and Environment applications – automated diary, etc.
   - Fancy voice control – e.g. Alexa/Siri and similar products
   - and many, many, other ubiquitous applications that could fill a whole supervision slot if I started listing them...

② *Describe how inference of activity can be done in mobile phone sensing applications.*

Gathering (labelled) data: User actions such as speech, motion, Wi-Fi, GPS, etc. and label data is gathered and a probabilistic ML model can be built. Each of the different sensor measurements can be grouped into a single feature vector and we can use something like SVM to perform classification/regression. (Alternatively, we can have separate learners for each sensor and ensemble these to infer the activity).

However, there are some issues:

- Noisy sensors and complex world data often cause confusion to the classic ML algorithms. Deep Learning and Deep Neural Networks could be helpful here, as they are more robust. However, their integration into mobiles and wearables is complicated because of resource constraints. There are attempts to overcome this both in terms of hardware (e.g. my phone has a dedicated Neural Processing Unit) and in terms of software (e.g. the paper by S. Bhattacharya and N.D. Lane).
- Gathering labelled data is also somewhat not straightforward, though more and more datasets are released for free use every day.
- There are always concerns about privacy of the user and similar law-related things.

③ *Describe what are the main challenges in running machine learning algorithms entirely on mobile devices.*

Building up on what I said in the previous question, I could add the following:

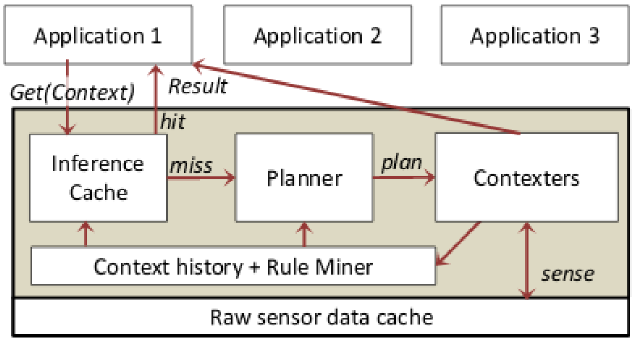
- Running ML/DeepL consumes a lot of power and drains battery – it might be beneficial to *sometimes* upload the sensed data and do the inference on the cloud. However, some other times, uploading itself may use a lot of resources so, it could be better to keep doing the computation on the device.
- Training models – at this moment mobile devices are not very capable of training a Neural Network from scratch, because they are limited in computational power (training the algorithm takes CPU power) and in memory (the more diverse the dataset, the better the results, the larger the memory needed to store it). E.g. imagine to have to train a model on Imagenet, but on a smartphone.

④ *Describe Context Sensing Sharing.*

The idea is that continuous sensing takes a lot of battery, whereas duty cycling may not give a good estimate of user actions. Therefore each time some app uses some sensor X, the OS caches it and when at a later time when another app uses the same sensor X the cache value is returned (assuming it's reasonably close in time, e.g. you can't use cached value of accellerometer 5 hours later).

Side Note: I understand that CrossApp Context Sharing $\neq$ Shared Context Sensing.

⑤ *Describe the architecture and components of ACE.*



1. Contexters – collection of modules, each of which determines the current value of a context attribute (e.g.,IsWalking) by acquiring data from necessary sensors and by using the necessary inference algorithm. An application can extend the contexters. Note that ACE treats contexters as black boxes; the only two pieces of information a contexter needs to expose to ACE are the name of the attribute that it determines (**IsWalking**, **IsDriving**, . . .), and its energy cost.

2. Raw sensor data cache – classic cache to share recent measurements.

3. Rule miner – The rule miner component of ACE maintains a history of timestamped tuples (e.g., **AtHome=True**), sensed for various applications. It then incrementally derives rules regarding relationships among various context attributes. It uses the Apriori algorithm for rule mining, which can efficiently discover association rules from databases containing transactions. Since in ACE various contexters may be invoked for different applications asynchronously[1], we need to batch them as a single transaction of co-occurring tuples. This could be done by:

    - Using a fixed time window – choosing the right window size is tricky
    - Using a dynamic window size – a default window size is used, but it's trimmed if the value of any context attribute changes, in order to avoid conflicting tuples in one window. Windows having a single tuple are also ignored.

    The rule miner also deals with inaccuracies (by regularly crossvalidating with ground truth) and also removes redundant rules by compacting them, in order to reduce inference overhead.

4. Inference cache – Used for intelligent context caching, e.g. if an app asks for the value of **Driving** but we have recently cached that **AtHome=True** then we can return **Driving=False**. We can reuse values not just for an exact lookup, but for semantically related lookup.

[1]To derive $A \Rightarrow B$, we need both A and B to appear together in the same transaction.

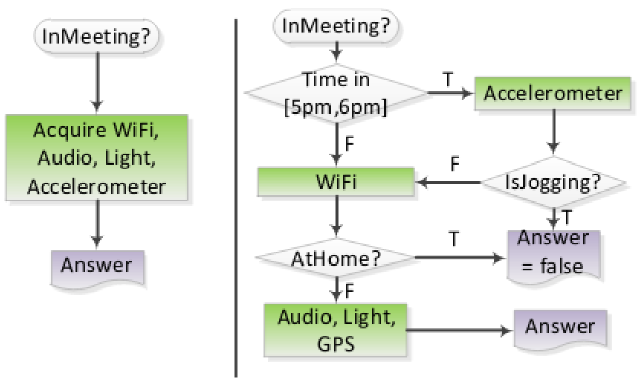
In terms of API it has a Get/Put interfaces, and whenever a Get(X) is in the cache, returns it. Get(X) also returns value of X if X is not directly in the cache but also, if it can be inferred by using context rules and cached values of other attributes

The inference cache uses expression trees (trees which represent boolean expressions) to efficiently exploit the rules. The expression tree is built in a way that can handle transitive relationships between the rules. One expression tree is maintained for each tuple, i.e. for **Driving=True** and **Driving=False** we have 2 trees. On a Get request of **X** both trees for it are evaluated and a result is returned.

As the expression trees could become really large and we want to reduce the memory overhead of using trees for the expressions, the trees are compacted using standard boolean algebra:

- Alternating AND-OR level.
- Absorption
- Collapse

5. Sensing planner – On a cache miss this finds the sequence of attributes to speculatively sense in order to determine the value in the cheapest way. The sensing planner can build a plan which orders the attributes to check based on their cost to sense and probability to be True (or False). E.g if we want to infer if the user is in a meeting, we can go for the 'classical' way or we can do a sequence of steps, through which we can infer the attribute in a cheaper way. Note that in the worst case, the path taken could be more costly than directly sensing the needed attributes, but ACE algorithms for speculative sensing minimize that probability.



⑥ *Illustrate the advantages of a dynamic offloading of computation model like in MAUI and the trade offs to be considered..*
Advantages:

- MAUI's primary goal is to reduce the energy consumption of mobile applications.
- In addition to saving energy, MAUI can also improve the performance of mobile applications.

- Allows developers to build applications that cannot currently be supported on mobile devices because of their resource requirements.

The trade offs to be considered are:

- *How much does MAUI reduce energy consumption of mobile applications?* — According to the MAUI paper, when the server is nearby the energy savings can reach one order of magnitude (10x). As the latency to the server increases, MAUI saves less energy. In fact, the energy consumed when offloading code over 3G is 2.5x higher than offloading code to a nearby server.

- *How Much Does MAUI Improve the Performance of Mobile Applications?* — For nearby servers and low latency, results showed that offloading improves performance. However, for a RRT higher than 25 ms, some apps' performance can be hurt (as the chess game experiments in the paper). The worst case performance is when offloading over 3G – the method for selecting piece in the chess game incurred 77% performance overhead, whereas the videogame incurred 54%.

- *Can MAUI Run Resource intensive Applications?* — Results showed that MAUI can bypass smarthone's limits on an application's memory footprint (e.g. there is a result, where peak memory consumption was 110MB whereas the phone had 32-48MB RAM).

- *What is the Overhead of MAUI's Optimizer?*[2] — Experiments showed that the solver takes 18ms on average to solve for a chess game and 46ms for the video game.

- *Is MAUI Effective at Identifying Code Offload Based on a Global View of a Program?* — Certain programs, e.g. face recognition, can have a functions that on their own execute using less resource/faster, but combined are better to be offloaded Compared to a naive solver, which views all methods locally, MAUI performed better.

- *How Effective are Incremental Deltas at Reducing MAUI's Data Transfer Overhead?*[3] — When experimenting with the videogame, MAUI reduced the amount of offloaded information by a factor of 2 (23KB to 12KB).

7. *The Bat system is a ToF (Tome of Flight) system where the tag acts as a transmitter.*

   i) *Explain how sync is obtained.*

   (A *sync*? I'm sorry for not being able to 'read between the lines' but can you clarify what is meant by sync.)

   A base station periodically transmits a radio message containing a single identifier, causing the corresponding Bat to emit a short unencoded pulse of ultrasound. Simultaneously, the ultrasound receivers in the rooms covered by the base station are reset via the wired

[2]Recall that MAUI has to profile the usage of the app and solve a 0-1 integer linear problem, in order to decide where it should execute the function.

[3]Deltas, i.e. transferring just state changes instead of entire state.

network. Receivers monitor the incoming ultrasound and record the time of arrival of any signal from the Bat. Using the speed of sound in air (which can be estimated from the ambient temperature), the times of flight of the ultrasound pulse from the Bat to receivers can be converted into corresponding Bat-receiver distances. The position of the object attached to the Bat can be then deduced by multilateration.

After a distance-measuring pulse has been emitted, the base station waits for reverberations of the pulse to die out before triggering another Bat, ensuring that receivers can ascribe incoming ultrasonic signals to the correct Bat. This process divides time into timeslots, each of which can be used to locate a single Bat. (Roughly 20ms per slot.)

ii) *Describe how to invert the system so that the tag is a receiver.*

That's a tricky one – when the Bat is a receiver you cannot just transmit from all transmitters, assuming transmitters are on the ceiling and that they use one and the same frequency. We need to do some 'hacks' in order to circumvent the fact that the Bat is a receiver:

- Let transmitters have a unique code (e.g. like a barcode of flickering sound or different frequency for each transmitter).
- Transmitters will transmit in time multiplexed manner – one transmitter per slot, there is always someone transmitting. Alternatively, they can transmit in a frequency multiplexed manner – one transmitter per frequency band, all transmitters transmit at once at the same time and then go silent for a period of δt.
- If we choose time-multiplexing, the Bat will need to be sensing all the time and remember which transmitters it heard (e.g. sensing 1, 5, and 6 one after the other). If we go for frequency multiplexing, the Bat will need to be sensing all the time for at least the synchronisation period when it enters the system. After that, it can infer and keep a schedule which is the same as the transmitters'. Alternatively, the schedule could be given to the bat by the base station.
- The Bat will need to have a mapping between the code of the transmitter and it's location and perform the relative multilateration computation itself. (I assume offloading of the data would be as expensive as the computation itself.)
- The Bat reports its location to the base station, in the case where we want the location to be open to other people (i.e. seeing when sb is in its office).

These should be enough for localising the Bat.

iii) *Discuss the advantages and disadvantages of this alternative approach.*

Disadvantages: Bat having to 'listen' (in FDM less frequently, but still...); Bat having to have a mapping and having to compute its own location (or do offloading of data). All of these 1) incur overhead, 2) waste Bat's battery life a lot more than the classic approach.

Advantages: Assuming the Bat is more like today's smartphones and the disadvantages are acceptable, we can handle as many Bats as we want, since the system is 'decentralised' (sort of) and the base station could handle many more devices.

8. *Imagine that you are tasked with designing an iPhone-like device that must be able to position itself at all times (indoors and out). Discuss the solutions you could use and the accuracies you might expect indoors and out.*

Outdoors:

Most likely, I would go for using GPS/GNSS. I would expect accuracy of around 3-4 meters (varies between exact solution used). Other tricks could give better accuracies, e.g. Carrier Phase positioning gives 20cm, but you need an accurate initial location and more time. Given it's an iPhone-like device, the user might be likely to want to use it immediately and keep walking while being guided with it, not to wait 15 minutes for an initial location.

Alternatives such as cellular localization may be an option, when GPS is not really suitable (e.g. you are in Manhattan, skyscrapers, you get it), but the accuracy from such methods is lower.

Indoors:

There are many alternatives. A first classic alternative would be to use BLE beacons. The device can detect the signal from the beacons and can calculate roughly the distance to the beacons to build an estimate for the location. Companies like Bloomberg have such things deployed for indoors localization. Accuracy can vary, but can be as good as 1.5m. (That's what I'd probably go for)

Another alternative would be using Wi-Fi to determine location – using some sort of Nearest Neighbour in Signal Space. This needs identifying signal at prespecified locations offline and then the mobile device can scan the Wi-Fi, build an observation vector and find the 'nearest' vector of the measurements. (Or you could use regression to create continuous probabilistic map for each base station.) Unfortunately, this approach suffers from several problems – poor geometry of APs, body shadowing, changing environments, scanning costs, room ambiguity (two rooms can have the same/similar measurements), etc.

Yet another WiFi solution could be FTM (Fine Timing Measurement), which assumes that phone and AP can be unsynced, but they have to have a good quality timing (i.e. fine timing). The localisation is done computing ToFs from different stations and use multilateration.

Optical solutions can also be an option, but it is going to be way too complicated to attach photosensors on the device (as in the Valve's Lighthouse product) and have lighthouses at different places on top of that.

There are other possible solutions as well, e.g. Phased Arrays, but I don't think they would be any better (needs evenly spaced antennas and reflection+mulitpath is a problem).

(I can't really find information what accuracies do the last solutions produce – can we just mention them on the supervision.)

9. *Describe the principles underlying the Kalman Filter. Why is it so commonly used? What does the H matrix in the Kalman Filter represent?*

At the start we have some Gaussian PDF estimating the initial position. As we move, we use the motion model to update the PDF and *predict* where we are. Motion model can vary between different examples, but should be possible to model it using linear algebra, e.g. $x_t = F_t x_{t-\delta t} + w_t$, where F_t is the matrix describing the motion model (can vary), xs are states in time and w_t is a noise term (can also vary). The uncertainty (which is modelled by a covariance matrix) needs also to be updated: $P_t = F_t P_{t-\delta t} F_t^T + Q_t$ (Q is a noise term).

Then we *predict* what would the measurements would be too, based on our belief about the state.

$$\mu_{expected} = H_t x_t$$
$$\Sigma_{expected} = H_t P_t H_t^T$$

The H matrix models how our state relates to the measurements (this could be as simple as (1 0) as in the lecture notes or could be complex if our measurment has different units/scale)

Then, given our measurements producing another μ_t and Σ_t (measurements have Gaussian PDF too) we will combine them by simply multiplying the two Gaussians together, which will produce another Gaussian, giving the probability both the expected and real measurements are true and *update* our belief for the state based on these probabilities[4].

The reasons KFs are commonly used is (quoting Dr R. K. Harle): "Because why not?". Everything boils down to linear algebra and matrix multiplications, for which a CPU is optimised for, i.e. they are cheap to compute. Moreover KF and EKF are algorithms and not heuristics, so as long as some preconditions, such as our system is a linear system with Gaussian noise, are met, KFs guarantee optimality.

10. *Discuss the extent to which you can speed up a particle filter using parallel processing.*

Clearly you can parallelise the UPDATE and CORRECT step, as the same operations are applied to each particle (in Flynn's taxonomy, it is SIMD). What is difficult to parallelise is the resampling step, where a CDF of the particles' probabilities has to be formed and this is not (easily) parallelisable. A quick search online led me to `https://docs.nvidia.com/cuda/cuda-samples/index.html#cuda-parallel-prefix-sum--scan-`, which *should* be an implementation of prefix sum, which should be enough for creating the CDF. Sampling can also be done in parallel. However, this is a solution for GPUs, not embedded CPUs as those on your phone, so it may not be very suitable solution.

[4] I'm referring to equations 14 to 19 in `http://www.bzarg.com/p/how-a-kalman-filter-works-in-pictures/`