MSc Project Offered in 2022-23:

1. A data-driven behavioural analysis of a cohort of people living with dementia

2. Orientation analysis in people living with dementia using in-home activity data

3. Using machine learning to analyse the risk of neuropsychiatric symptoms in people with dementia

4. Neuroscience inspired continual machine learning

Project Details:

1. A data-driven behavioural analysis of a cohort of people living with dementia

People living with dementia are among the most vulnerable population group, with 50% requiring hospitalisation due to adverse health events. Remote monitoring technologies allow us to observe and measure the behaviours of people living with dementia in naturalistic settings. This project will focus on how we can use data analytics and machine learning methods to augment the in-home monitoring process and shift from reactive to proactive care.

Exploratory analyses will be conducted, and machine learning models designed on data collected as part of the UK Dementia Research Institute Care Research and Technology Centre's ongoing Minder study. The Minder study dataset is comprised of more than 50,000 days and 30,000 nights of data from more than 140 participants, all with an established diagnosis of dementia or mild cognitive impairment. This dataset contains information on activity from passive infrared sensors, physiological measurements (such as heart rate and body temperature) and sleep recordings, as well as daily wellness questionnaire responses and several labelled data for verified health-related incidents.

This research will focus on identifying and developing simple analytical models that can proactively detect changes in daily routines. If the preliminary results are encouraging, these models could be deployed in our study platform to raise flags for possible health-related incidents.

Supervisor: Payam Barnaghi
Co-supervisor: Nan Fletcher-Lloyd
Keywords: Data Analytics, Machine Learning
Desirable skills: Python

2. Orientation analysis in people living with dementia using in-home activity data

The Minder Health Management study currently uses eleven regular cognitive assessment scales and questionnaires to understand and interpret the progression of the physical and cognitive health of people living with dementia. For the participants of the study, there are six assessments that occur once every 6 months. We also ask the study partners to complete an additional three assessments about the participant; two of these scales are also asked once every 3 months. The following scales contain sub-components that assess participants' spatial and temporal orientation:

- The Alzheimer's Disease Assessment Scale–Cognitive Subscale (ADAS-Cog) the participant is asked their name, the day of the week, month, year, place, and time of day. The scoring range is from 0 to 5. This is conducted once every six months [1].

-The Standard Mini-Mental State Exam (SMMSE), the participant is asked the year, month, season, date, day of the week, time of day, country, county, town, address, and room/building. Scoring range is 0 to 10. This is conduced once every twelve months [2].

- When SMMSE cannot be used, the Telephone Mini-Mental State Exam (TMMSE) is used. For example, when there is limited access to participants e.g., during the Covid-19 pandemic. Scoring for this is 0 to 9 [3].

- The Bristol Activities of Daily Living Scale (BADL) has five sub-components that can be used to assess orientation. These include orientation to space, orientation to time, games & hobbies, driving & using public transport, and managing finances. Each sub-component is scored from 0 to 5. This is conducted once every three months [4].

- The Neuropsychiatric Inventory (NPI) asks the study partner to identify any night-time behaviours of the participant. Scoring for this includes the sum of each night-time behavioural disturbance as well as the frequency and severity that the participant exhibits that behaviour. This is conducted once every three months [5].

- The Pittsburgh Sleep Quality Index (PSQI) assesses the participant's sleeping habits. This asks about sleep duration, quality, latency, efficiency, disturbances, use of sleeping medication and daytime dysfunction. The scoring range for this is the sum of each component. This is conducted once every six months [6].

Combining sub-components from different scales allows us to evaluate the participants' spatial and temporal orientation. The PSQI can also be used to identify any night-time wandering and if any sleep disruption may contribute to disorientation to either time, space, or both.

Complementary to this, we also collect activity data within the participants' homes, from the study's in-home monitoring technology and devices. Each room in the house contains a Passive InfraRed (PIR) sensor that records movement. Each participant also has a sleep mat that monitors an extensive range of sleep data, including the frequency at which one leaves and enters the bed and the sleep state.

Therefore, using data from participants that live alone, we have an opportunity to verify any changes in spatial/temporal orientation from corresponding sub-components of the assessment scales, with the in-home monitoring data. For example, we might expect participants who become more spatially disorientated may wander more in familiar surroundings. This can be verified using sleep mat data and PIR sensor data, where we might expect an increase in activity and frequency. Similarly, participants who become more temporally disorientated may exhibit more night-time wandering and score more severely in ADAS-Cog, MMSE, BADL, NPI and PSQI sub-components.

Supervisor: Payam Barnaghi
Co-supervisor: Chloe Walsh
Keywords: Cognitive assessments, temporal and spatial orientation, dementia, data analysis
Desirable skills: Python and data visualisation, statistical inference.

References

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6. Buysse DJ, Reynolds CF, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193-213.

3. Using machine learning to analyse the risk of neuropsychiatric symptoms in people with dementia

This project will make use of existing datasets, made available by our ongoing research (2019-2028), to study key factors that can be used to develop predictive models for neuropsychiatric episodes.

The dataset comprises daily data from 140 participants with various types of dementia over a 3-year period. This dataset includes physiological measurements (blood pressure, body temperature, heart rate, etc.), sleep recordings, movement and environmental data from passive infrared sensors, and routinely collected questionnaires and assessments, as well as associated labels (agitation, delirium, sleep disorder, etc.) for the reported health-related events and verified observations.

Using these data, you will be able to build and apply machine learning models to identify possible episodes of neuropsychiatric symptoms. When working with these data, you need to overcome several challenges:

- Labels for neuropsychiatric events are unbalanced, sporadic, and sparse;
- Correlated data can also contain missing values and originate from sources with different granularities.

Supervisor: Payam Barnaghi
Co-supervisor: Francesca Palermo
Keywords: Neuropsychiatric symptoms, dementia, predictive models, risk analysis.
Desirable skills: Python and data visualisation.

4. Neuroscience inspired continual machine learning

Continual learning is a crucial area of machine learning focused on building networks that can continue to adapt to new tasks, environments, or instances – becoming lifelong learners. The problem of catastrophic forgetting is one of the main obstacles in achieving a lifelong learner, since models trained on new tasks erase their knowledge of previously seen tasks.

Continual learning focused neural networks, inspired by biological processes is an interesting and developing area of machine learning. Recent work by DeepMind studied the use of Dendritic Gated Networks [1], built on research done on Gated Linear Networks [2] and inspiration from the biological neuron. Both works make use of a local learning technique (as an alternative to backpropagation), in an effort to research more biologically plausible learning algorithms by updating weights based on the loss between the layer output and the target, rather than a backpropagation of loss between the network output and the target. Since both works also make use of input-controlled gating, they allow for subnetworks based on inputs, and so naturally tackle the challenge of catastrophic forgetting (a key obstacle in building life-long learning networks). Both techniques improve the continual learning ability of networks without having to specify that a new task is being shown.

This work is related to that done by Iyer, Grewal, and Velu *et al.* [3], who study the use active dendrites to alleviate catastrophic forgetting by learning a mapping between inputs and context vectors, which in turn gate the weights of network layers to produce subnetworks specialised to a given task. This work shows experimentally that the network can perform well when the task is known to have changed, and when the task identities are not given.

The proposed project would focus on expanding the work of any of the research discussed above and would focus on building networks that are robust to forgetting previous tasks, using techniques inspired by biology. It is an open project, and the student is welcome to take the research in a direction that complements their skillset. The datasets used for this analysis would be centred around the continual learning literature and would not be based on biology.

Supervisor: Payam Barnaghi
Co-supervisor: Alex Capstick: PhD student with a background in Mathematics and Machine Learning
Keywords: Neuroscience inspired machine learning, theoretical machine learning, continual learning, .
Desirable skills: Python, machine learning concepts and mathematics, experience with Pytorch or TensorFlow

References
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3. Iyer A, Grewal K, Velu A, Souza LO, Forest J, Ahmad S. Avoiding Catastrophe: Active Dendrites Enable Multi-Task Learning in Dynamic Environments. Frontiers in neurorobotics. 2022;16.

Further information:

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