# Prediction of hyperglycaemia and hypoglycaemia events using longitudinal data

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**Abstract**

**In type 1 diabetes management, mobile health applications are becoming a cornerstone to empower people to self-manage their disease. There are many applications addressed to calculate insulin doses based on the current information (e.g. carbohydrates intake) and a few of them are accompanied by modules able to supervise postprandial conditions and recommend corrective actions if the user falls in an abnormal state (i.e. hyperglycaemia or hypoglycaemia). On the other hand, mobile apps favour the gathering of historical data from which machine learning techniques can be used to predict if user conditions will worsen.**

**This work presents the application of k-nearest neighbour on the historical data gathered on patients, so that given the information related to a sequence of meals, the method is able to predict if the patient will fall in an abnormal condition. The experimentation has been carried out with the UVA-Padova type 1 diabetes simulator over eleven adult profiles. Results corroborate that the use of sequential data improve significantly the prediction outcome when forecasts distinguish the type of meal (breakfast, lunch and dinner).**

## Introduction

Type 1 Diabetes Mellitus (T1DM) is a chronic disease that demands a strict control of the Blood Glucose (BG) level of the patient. This BG control is required to avoid hypoglycaemia or hyperglycaemia events, which are associated to serious short-term and long-term complications, e.g. coma, blindness, sever kidney failure or even death.This paper studies how sequences of data (recorded by T1DM people) can be used to predict hypoglycaemia and hyperglycaemia events using the k-nearest neighbours (k-NN) method.

## Methodology

In the problem faced in this paper, the following information is available: Time (T) in minutes; Carbohydrate (CH) intakes (mg); Bolus insulin dose (B);CGM readings (mg/dL). This information is used to create an event for each meal.

| T | CH | B | CGM | Class |
|---|---|---|---|---|
| Day 1 07:16 | 3866.7 | 3.36 | 139.52 | Hypo |

Meal data (breakfast/lunch/dinner)

**Table 1:** Structure of a meal event

Given the set of meal events, these are sorted according to the time attribute and processed to create sequences of meals where each sequence contains all the ordered meals of a time window of x hours.

One-shot data:

| | |
|---|---|
| day1 07:16 Breakfast data | Hypo |
| day1 13:58 Lunch data | Non Hypo |
| day1 18:16 Dinner data | Non Hypo |
| day2 07:25 Breakfast data | Non Hypo |
| day2 13:08 Lunch data | Hypo |
| day2 18:50 Dinner data | Non Hypo |

Sequence of 24 hours data:

| | | | |
|---|---|---|---|
| day1 07:16 Breakfast data | day1 13:58 Lunch data | day1 18:16 Dinner data | Non Hypo |
| day1 13:58 Lunch data | day1 18:16 Dinner data | day2 07:25 Breakfast data | Non Hypo |
| day1 18:16 Dinner data | day2 07:25 Breakfast data | day2 13:08 Lunch data | Hypo |
| day2 07:25 Breakfast data | day2 13:08 Lunch data | day2 18:50 Dinner data | Non Hypo |

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**Figure 1:** Example of the sequence generation of 24 hours

The class of each sequence of meals is labelled according to the postpandrial status (PS) of the last meal of the sequence, following two procedures:

- PS is labelled as hypoglycaemia if a CGM reading between 2 and 6 hours after the bolus administration is below 70 mg/dl, otherwise it is labelled as non-hypoglycaemia.
- PS is labelled as hyperglycaemia if CGM readings are above 180 mg/dl during at least 60 minutes between 2 and 6 hours after the bolus administration, otherwise it is labelled as non-hyperglycaemia.

These sequences are then used to predict the class of a given sequence of meals using KNN, where $k < sqrt(n)$ (n is the number of examples).

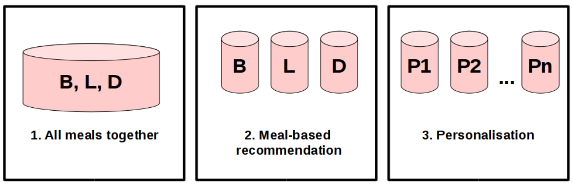


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**Figure 2:** Three different scenarios that have been implemented to analyse different hypothesis, where B is Breakfasts, L is Lunchs, D is Dinners, and P is a Patient

For each scenario, we have compared the one-shot (entries with only one meal) with our sequential data approach (sequences of 4x24 hours).

## Results

**TPR: True Positives Rate FNR: False Negatives Rate FPR: False Positives Rate**

**Accuracy = (True Positives + True Negatives)/(total number of instances)**

**Validation: 10 cross-validation folds**

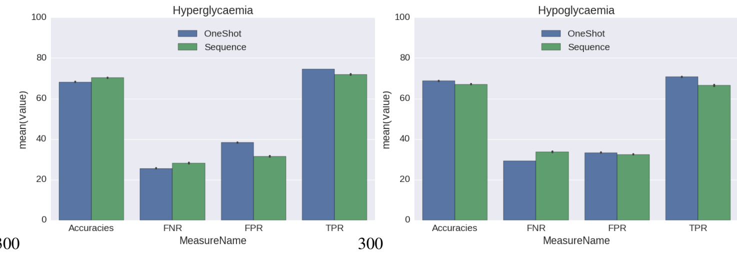


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**Figure 3:** All meals together. Results obtained using temporal data with the proposed methodology (sequences) and without using temporal data (one-shot)

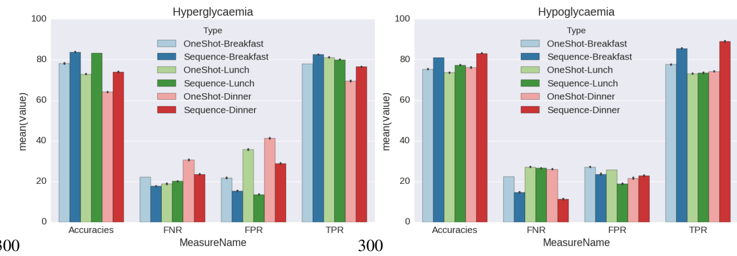


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**Figure 4:** Meal-based recommendation. Results of the meal-based recommendation with sequences and one-shot data.

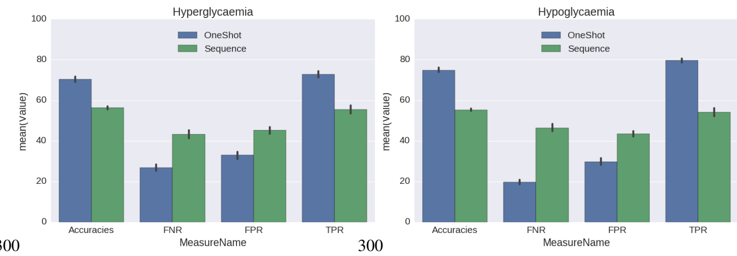


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**Figure 5:** Personalisation (all meals together).

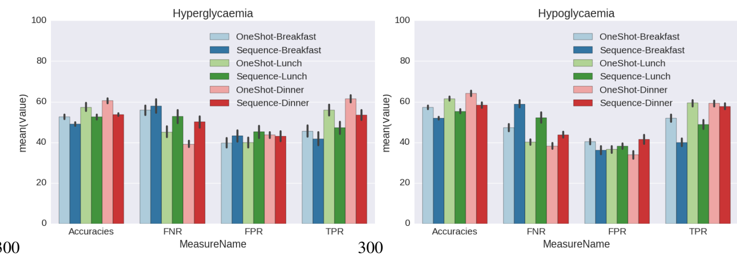


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**Figure 6:** Personalisation (meal-based recommendation).

## Conclusions

1. Recommendations based on meals increases the overall performance (TPRs up to 0.88 and accuracies up to 83% have been achieved, while FNR and FPR are significantly lower, from 0.25 to 0.11). Furthermore, the use of sequential data clearly outperforms the one-shot data.
2. Recommendations should be based on type of meal (do not merge all the meals together).
3. Personalized databases with less amount of registers, does not favour nor the use of sequences, neither the distinction of different types of meals.

## Forthcoming Research

- Eager mechanisms or its hybridization for sequence learning
- Fuzzy approach in the labelling

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ATTD Advanced Technologies & Treatments for Diabetes

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