Predicting Blood Glucose Levels for Diabetics

Pedro Salgado (psalgado@stanford.edu), Diego Zavala (dzavalag@stanford.edu)

Project for CS230

Link to see the presentation
https://vimeo.com/340587300

Motivation

- According to CDC, +100 million adults in the US lived with diabetes or prediabetes, disease that limits life conditions of patients and put on risk their life is mismanaged
- Diabetics patients use manual monitoring systems to use insulin self-injections and control the level of glucose in the blood (CGM)
- By accurately predicting the level of glucose in a systematic basis, patients could improve their life conditions and prevent health risks

Data

- We used Diego's personal CGM and insulin pump records from last 4 months between December '18 and March '19, totaling ~35k observations, including:

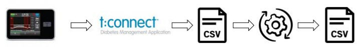
1. Blood glucose levels (every 5 minutes)
2. Insulin infusions, including the basal rate (not frequently adjusted) and "bolus"
3. Carbohydrates eaten

	Time_EventDateTime	Id	Real	Date	CGM	Insulin_Basal	Insulin_bolus	Carbs
0	2018-12-01 00:00:12	1	1	2018-12-01	118.0	0.10	0.0	0
1	2018-12-01 00:05:12	2	1	2018-12-01	127.0	0.09	0.0	0
2	2018-12-01 00:10:12	3	1	2018-12-01	130.0	0.09	0.0	0
3	2018-12-01 00:15:12	4	1	2018-12-01	128.0	0.09	0.0	0
4	2018-12-01 00:20:12	5	1	2018-12-01	124.0	0.09	0.0	0

- Based on Li et al ('18) and Lai et al ('18):

1. The state-of-the-art solution seem to be a combination of CNN and RNN, with a RMSE of 21.1 and 33.3% for 30-minute and 60-minute, respectively
2. 5 minutes is the optimal step for data series
3. Total number of lags may vary depending om time prediction (30 to 90 minutes)

Features



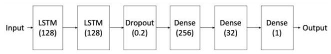
- The process of data collection and preparation include the following steps:

1. Upload the insulin pump information to the t:connect diabetes management application. The application is provided by Tandem.
2. From t:connect we download a csv file with raw data, including 3 data tables: one with the glucose level observations (every 5 minutes), other with the basal rates (every time it changes), and other with the insulin bolus and carbs (when bolus was applied)
3. The 3 tables are consolidated in one, interpolating data if missing value, or blank otherwise. The basal rates, insulin bolus and carbs are re-calculated to 5-minute slot

- After the data processing, the data is scaled, randomized and splited between train (72.25%), dev (12.75%) and test (15%) sets

Results

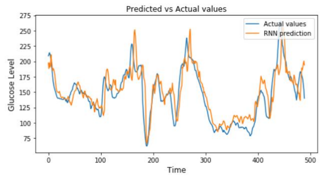
- We compared a Recurrent Neural Network with 2 baseline models: naive and ARIMA
- The architecture used in the RNN was

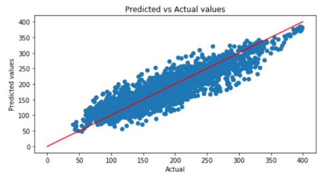


- The results were:

Method	Result (RMSE, mg/dL)
Naive	32.117
ARIMA	54.2
RNN	24.578

- The best method was the RNN. Below are some comparisons of the predicted vs. the actual values





Conclusion

- In this project, we use a RNN to predict the blood glucose level of a diabetic person taking as input the previous blood glucose level, insulin infused and carbs eaten.
- The results of the RNN model are better than the baseline models (Naive and ARIMA), but not superior than those found in the literature.

Future Work

- Compare the use of several patients data to train a general model than can be customized as a second step to a particular patient
- Incorporate physical activity indicators as inputs in the model using information from wearable devices, such as a Fitbit or Apple Watch

References

- Anitha, P. V. ('06). Application of a radial basis function neural.
- C. Zecchin, A. F. ('09). A new NN approach for short-term glucose prediction using CGM time-series and meal information.
- Guokun Lai, W.-C. C. (2018). Modeling Long- and Short-Term Temporal Patterns with Deep NN.
- Kezhi Li, J. D. (2018). Convolutional Recurrent NN for Glucose Prediction.
- Raj, M. (2018). Diabetes Prediction- Artificial NN Experimentation.