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A Sparse Coding Based Approach for Automatic Diet Monitoring with Continuous Glucose Monitors

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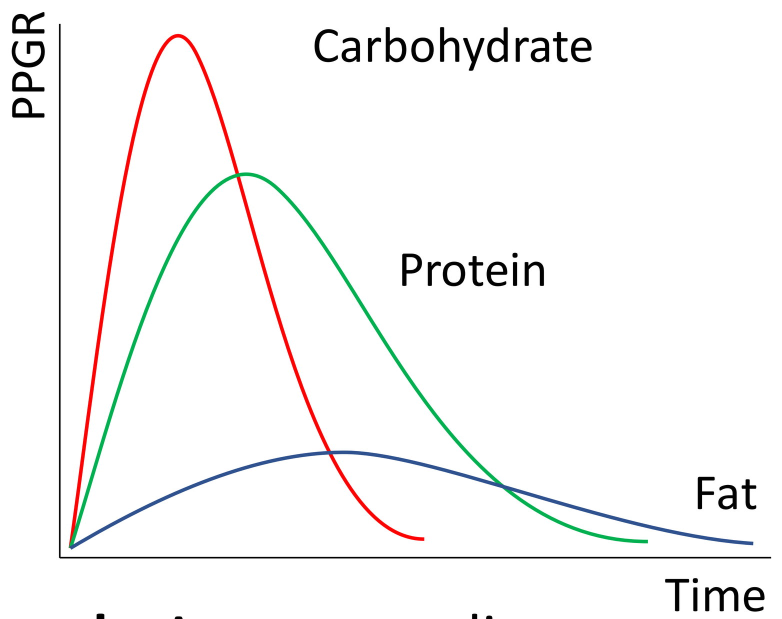
Introduction

- Monitoring diet intake is essential to prevent the onset of diseases such as obesity, type 2 diabetes (T2D) [1]
- Conventional methods of monitoring diet intake include recording food diaries which can be cumbersome to the user and also unreliable.
- Continuous glucose monitors measures glucose in the interstitial fluid using an electrode inserted in the skin. We use CGM to record the postprandial glucose response (PPGR).

- **Key Idea:** PPGR of a meal depends on the macronutrient concentration of the meal [2]. Therefore, shape of the PPGR can be used to recover the macronutrient composition of the meal.



- **Proposed Approach:** A sparse coding approach to estimate macronutrients from PPGR. Represent the PPGR of a meal as a sparse combination of meals in a dictionary. Then combine the sparse weights with the macronutrients in the dictionary's meals to estimate the macronutrients of the test meal

Methods

- X_{ms} dictionary containing meals from S subjects after consuming M different meals
- $X_{m's'}$ PPGR of a new subject s' that has consumed meal m'
- Represent new meal as a combination of meals in dataset X

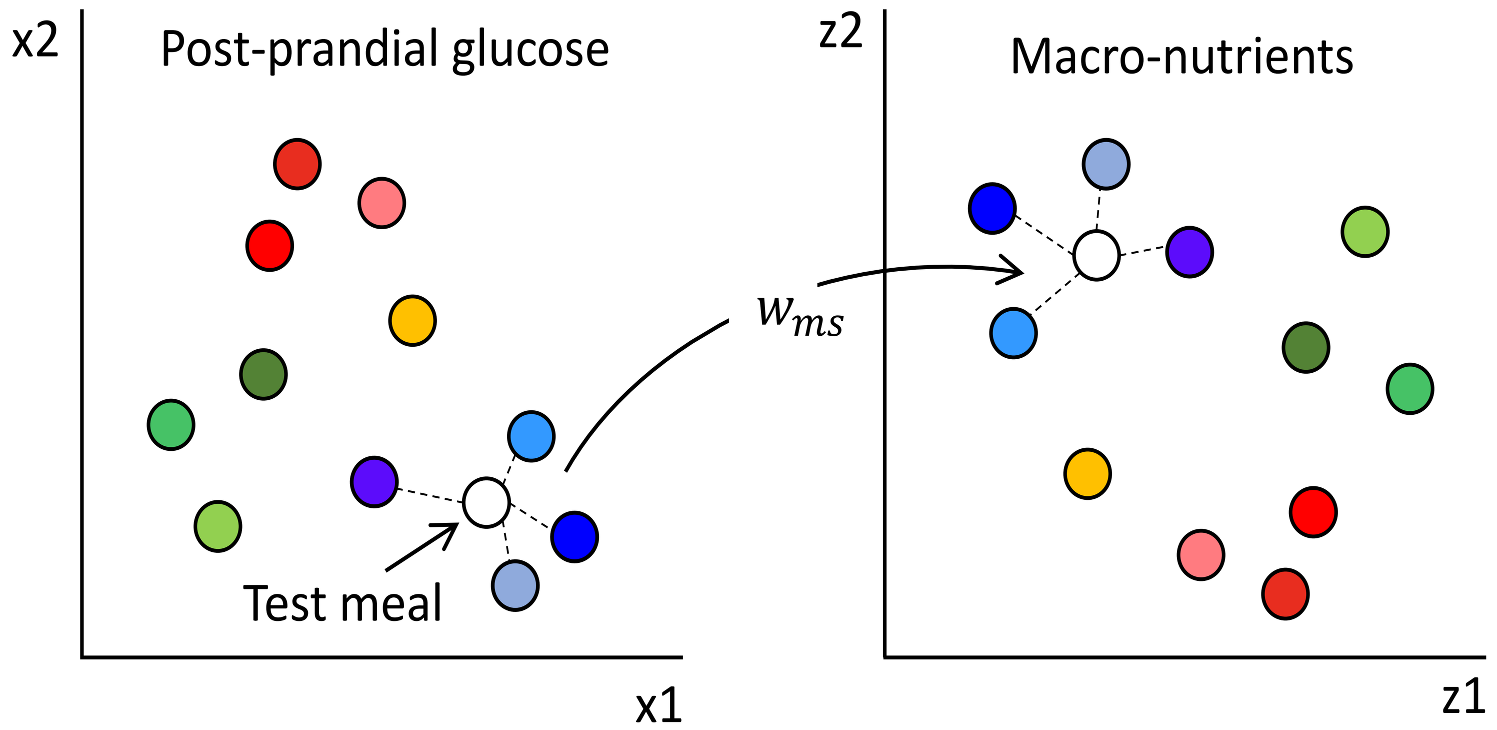
$$X_{m's'} \cong \sum_{s}^{S}\sum_{m}^{M} w_{ms}X_{ms}$$

- Learn weights w_{ms} using Lasso regularization
- $w_{ms} = argmin\,\{\|X_{m's'} - \sum_s^S \sum_m^M w_{ms}X_{ms}\|^2 + \lambda\|w_{ms}\|_1\}s.t.\,w_{ms} \geq 0$
- Normalize the learnt weights

$$\widehat{w}_{ms} = w_{ms}/\sum w_{ms}$$

- $Z_{m's'}$ macronutrient composition of meal m' and subject s'

$$Z_{m's'} \cong \sum_{s}^{S}\sum_{m}^{M} \widehat{w}_{ms}Z_{ms}$$



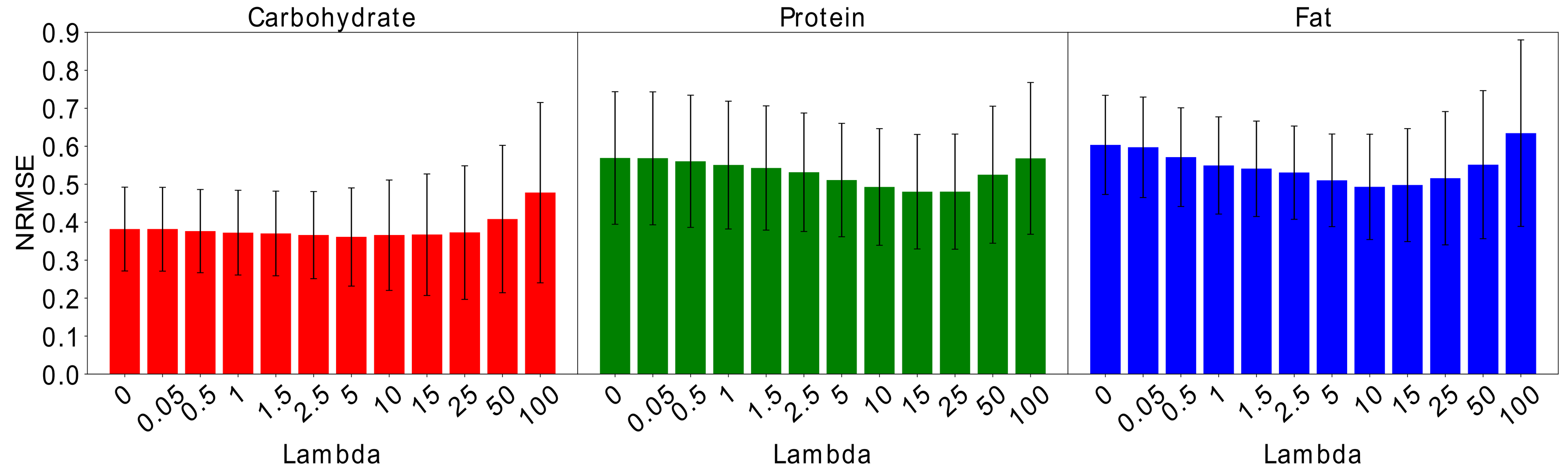
Dataset

- 15 subjects (60-85 years) and BMI 25 – 35
- Each subject took part in 9 study days where they consumed meals with different amounts of macronutrients

Meal	Carbohydrate (g)	Protein (g)	Fat (ml)
C1P1F1	52.25	15	13
C2P2F2	94.75	30	26
C3P3F3	179.75	60	52
C1P2F2	52.25	30	26
C3P2F2	179.75	30	26
C2P3F2	94.75	60	26
C2P1F2	94.75	15	26
C2P2F3	94.75	30	52
C2P2F1	94.75	30	13

Results

Evaluation metric: NRMSE $= \left(\frac{1}{N}\sum(y-\hat{y})^2/y^2\right)^{1/2}$,



- Leave one subject out (LOSO) :Train on 14 subjects and test on the 15th subject

	Pooled correlation			Average RMSRE		
Method	C	P	F	C	P	F
Proposed	**0.49*** **	**0.28** **	**0.39*** **	**0.37**	**0.49**	**0.48**
RR	0.39***	0.12	0.24**	0.45	0.71	0.60
LDA-kNN	0.36***	0.05	0.28**	0.48	0.64	0.67

- Leave one meal out (LOMO):- Train on 8 meals and test on the 9th meal

	Pooled correlation			Average RMSRE		
Method	C	P	F	C	P	F
LOSO	0.49***	**0.28** **	**0.39*** **	**0.37**	**0.49**	**0.48**
LOMO	**0.5*** **	0.07	0.24**	0.41	0.7	0.64

Conclusion

- The sparse method outperforms two supervised methods on a subject independent task. The performance on the subject independent task is better compared to a subject dependent task
- The sparse method performs better on predicting carbohydrates compared to proteins and fats

Acknowledgement

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References

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[2] Thomas MS Woleverand Claudia Bolognesi, "Prediction of glucose and insulin responses of normal subjects after consuming mixed meals varying in energy, protein, fat, carbohydrate and glycemic index," The Journal of nutrition, vol. 126, no. 11, pp. 2807–2812, 1996.