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

- \(X_{m's}'\) dictionary containing meals from S subjects after consuming M different meals
- \(X_{m's}'\): PPGR of a new subject's meal that has consumed meal m'

Acknowledgement

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Results

- Leave one subject out (LOSO): Train on 14 subjects and test on the 15th subject
- Leave one meal out (LOMO): Train on 8 meals and test on the 9th meal

<table>
<thead>
<tr>
<th>Method</th>
<th>Carbohydrate</th>
<th>Protein</th>
<th>Fat (ml)</th>
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<tr>
<td>Proposed</td>
<td>0.49***</td>
<td>0.28**</td>
<td>0.39***</td>
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<td>RR</td>
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<td>LDA-kNN</td>
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<td>0.05</td>
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<tr>
<td>LOMO</td>
<td>0.5***</td>
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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

References