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Modelling fat mass as a function of weekly physical activity profiles measured by Actigraph accelerometers

Nicole H. Augustin[1], Calum Mattocks[2], Ashley R. Cooper[2],
Andy R. Ness[3] and Julian J. Faraway[1]

[1] Department of Mathematical Sciences, University of Bath, Bath, UK;
Emails: n.h.augustin@bath.ac.uk ; j.j.faraway@bath.ac.uk;
[2]School for Policy Studies, University of Bristol, 8 Priory Road, Bristol;
Emails: c.mattocks@bristol.ac.uk, ashley.cooper@bristol.ac.uk;
[3] Department of Oral and Dental Sciences, Bristol Dental Hospital; Email:
Andy.Ness@bristol.ac.uk.

Abstract.　　We show results on the Avon longitudinal study of parents and children (ALSPAC) using a new approach for modelling the relationship between health outcomes and physical activity assessed by accelerometers. The key feature of the model is that it uses the histogram of physical activity counts as a predictor function, rather than scalar summary measures such as average daily moderate to vigorous physical activity (MVPA). Three models are fitted: (1a) A regression of fat mass at age 12 (N = 4164) onto the histogram of accelerometer counts at age 12; (1b) A regression of fat mass at age 14 (N = 2403) onto the histogram of accelerometer counts at age 12 and (1c) a regression of fat mass at age 14 (N = 2413) onto the accelerometer counts at age 14. All three models significantly improve on models including MVPA instead of the histogram and improve the goodness of fit of models 2a, 2b and 2c from R^2 = 0.267, 0.248 and 0.230 to R^2 = 0.292,0.263 and 0.258 for models 1a, 1b and 1c respectively. The proportion of time spent in sedentary and very light activity (corresponding to slow walking and similar activities) has a positive contribution towards fat mass and time spent in moderate to vigorous activity has a negative contribution towards fat mass.

Keywords: Accelerometer; ALSPAC; ambulantory monitoring; functional data analysis; generalised regression of scalars on functions; histogram; physical activity; obesity.

1. Introduction

In the epidemiological setting where physical activity may be a health outcome or the predictor of a health outcome, the accelerometer activity counts are traditionally summarised into a single summary statistic (summary) per individual, e.g. total activity, defined as the average accelerometer counts per minute (mean cpm); average daily moderate to vigorous physical activity (MVPA), defined as the average minutes per day spent at moderate or vigorous activity; or average sedentary behaviour, defined as the average minutes per day spent in sedentary activity (Riddoch et al., 2009; Mitchell et al., 2009, 2011). For each of these summaries cut-points of counts per minute are used corresponding to light, moderate and vigorous activity, either based on findings in the literature or on calibration studies (Mattocks et al., 2007; Treuth et al., 2004; Puyau et al., 2002).

Using summaries of specific activity levels such as MVPA as predictors in a model requires adjusting for summaries of activity levels at the remaining activity range. But this can be problematic due to collinearity, as although some of these summaries are confounders of each other, adjusting for remaining activity levels may lead to poor and unreliable parameter estimates with large variances due the fact that these variables are not independent of each other. For example, MVPA is highly correlated with total activity as one variable is contained in the other. In addition, using only scalar summaries ignores the distribution of the activity counts per minute. A further problem with the traditional approach of using scalar summaries is that it relies on making assumptions about cut-points for different activity levels (light, moderate, vigorous). The assumptions may not always be met, for instance there is some debate whether the cut-points and hence their equivalent estimate of energy expenditure change with age, in particular for children going through adolescence (Reilly et al., 2006).

Our aim is to improve the traditionally used approach of using scalar summaries of physical activity counts in statistical models. To achieve this aim we investigate the relationship between fat mass and the entire distribution of physical activity counts with a cut-point independent approach. Our data are from the Avon longitudinal study of parents and children (ALSPAC) (Golding et al., 2001). In ALSPAC physical activity counts are available at three ages, 12, 14 and 16. Here we consider ages 12 and 14. Counts are recorded over 7 days resulting in 10080 observations per individual and occasion. As the raw accelerometer counts cannot be directly compared between individuals we summarise them with a histogram and use the histogram as a predictor in a statistical model. Hence the objective is to estimate the contribution each part of the histogram has on fat mass as a smooth function, and in particular whether the estimates are different between the age 12 and 14. By estimating these contributions as a smooth function we avoid any collinearity problems we would introduce by including single summaries covering the entire intensity range of physical activity (i.e. average proportion time spent in sedentary, light, moderate and vigorous activity).

The motivation for using fat mass as a health outcome is because it is a measure of obesity and it is strongly associated with other health outcomes such as cardio-metabolic health (cardiovascular disease and type 2 diabetes) (Haslam and James, 2005). We consider fat

mass at ages 12 and 14 with physical activity at ages 12 and 14 as predictors, since physical and sedentary activity in youth is a cause of early onset obesity which is associated with adulthood obesity (Yang et al., 2006). There are cross-sectional and prospective associations between physical activity (estimated by MVPA and total activity) and fat mass (Ness et al., 2007; Riddoch et al., 2009).

2. Data and pre-processing

Our data are from the Avon longitudinal study of parents and children (ALSPAC). This is a birth cohort study with 14 541 pregnant woman enrolled; see for example Golding et al. (2001) for a detailed description. Fat mass, the outcome, was derived using a Lunar Prodigy DEXA scanner. All children of the study have been invited to regular research clinics from the age of 7. At the ages of 12, 14 and 16 the children attending these clinics were asked to wear an MTI Actigraph AM7164 2.2 Accelerometer for 7 days set to an epoch time of 1 minute. At age 14 children were wearing either the AM7164 or the GT1M Actigraph. Physical activity, the predictor, is a time series of 10080 minute by minute accelerometer measurements of counts per minute over 7 days available at three ages (12, 14 and 16). In addition the children's height was measured. Children wore the accelerometer during waking hours, except for showering, bathing, swimming and any water sports. As confounder variables we use only height, height^2, sex and weartime (mean minutes per day). Adjustment for height was to normalise fat mass for stature, and height squared was used as there is evidence of a non-linear relation between fat mass and height. Other possible confounding variables are maternal education, maternal smoking during pregnancy, maternal obesity and pubertal stage. Previous analysis (Riddoch et al., 2009) found almost no change in parameter estimates when analysing the same data adjusting for these additional variables, hence we only report results for the minimal adjustment. Since our motivation is mainly about the improvement of the traditionally used summaries of physical activity we concentrate on the data for ages 12 and 14 with fat mass as a response, a rigorous analysis using a longitudinal model incorporating the traditionally used summaries of physical activity of the of ages 12 and 14 is reported in Riddoch et al. (2009). The maximum counts per minute observed above 15000 cpm were set to missing, as it is unclear what activity would result in such a high count and it is more likely that these high counts were caused by vibrations, from e.g. car journeys, which the actigraph software failed to filter out. Counts observed above 8000 cpm were truncated to 8000 in order to avoid problems caused by very small numbers of observations. For the remaining pre-processing of the raw accelerometer data we followed Mattocks et al. (2008). That is: Any sequence with more than 10 zeros was replaced by missing values, since these periods were regarded as periods when the monitor was not worn; days with a mean count less than 150 or a mean count of three standard deviations above the overall mean (prior to exclusions) were invalid; only days were included if the monitor was worn at least 10 hours; weekly profiles were invalid if less than 3 valid days were observed.

3. Summary and exploratory statistics

Not all of the children who had their fat mass measured by scanner also had their physical activity measured and vice versa. Following the processing protocol of the accelerometer data this yields N = 4164 children with both measurements at age 12 and N = 2403 children at age 14.

Table 1. Summary statistics.

	N	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
females at 12								
fat (kg)	2201	2.29	7.87	12.75	11.24	16.12	43.08	6.51
age	2201	10.6	11.6	11.8	11.8	11.9	14.4	0.3
height	2201	1.28	1.46	1.52	1.51	1.57	1.77	0.07
bmi	2201	12.4	16.7	19.2	18.6	21.0	36.4	3.4
cpm	2201	218	442	546	524	630	1297	149
MVPA	2201	0.43	9.57	18.11	15.67	24.33	77.14	11.54
females at 14								
fat (kg)	1280	3.49	10.69	16.07	14.75	19.96	58.19	7.27
age	1280	12.94	13.7	13.8	13.8	13.9	14.9	0.2
height	1280	1.42	1.58	1.62	1.62	1.66	1.84	0.06
bmi	1280	14.07	18.16	20.54	20.02	22.23	38.61	3.38
cpm	1280	175.57	372.22	483.72	457.73	564.42	1201.94	154.67
MVPA	1280	0.14	9.00	19.80	16.37	26.89	113.57	14.84
males at 12								
fat (kg)	1963	1.54	5.51	10.20	8.28	13.18	40.77	6.42
age	1963	10.75	11.61	11.78	11.73	11.88	14.12	0.29
height	1963	1.26	1.45	1.50	1.50	1.55	1.84	0.07
bmi	1963	12.78	16.42	18.68	17.94	20.28	33.21	3.11
cpm	1963	245.13	527.95	660.80	641.75	770.83	1519.96	185.96
MVPA	1963	0.60	16.00	28.82	25.60	38.50	125.50	17.09
males at 14								
fat (kg)	1123	2.25	5.52	10.66	8.35	13.98	41.05	7.07
age	1123	12.63	13.74	13.84	13.82	13.91	14.91	0.18
height	1123	1.32	1.59	1.65	1.65	1.71	1.93	0.09
bmi	1123	13.76	17.54	19.73	19.14	21.30	33.68	3.05
cpm	1123	193.74	459.82	599.14	572.70	710.71	1495.19	192.08
MVPA	1123	0.50	15.67	29.49	26.00	39.75	104.33	18.55

The distribution of the outcome variable fat mass (kg) is right-skewed (Table1). There is a difference between girls and boys with girls having a higher fat mass and this difference becomes more pronounced at age 14. Total activity (cpm) decreases between age 12 and 14 for males and females whereas MVPA increases between age 12 and 14. Both cpm and MVPA are higher on average for boys.

For the histogram summaries of physical activity we first raise the activity counts to the power of 0.35 in order to reduce the extreme skewness of the activity counts distribution. We then transform the profiles to activity level histograms, thereby making profiles comparable between individuals, reducing the dimension of data, but maintaining interpretability. Investigating the median histograms of males and females at age 12 in Figure 1 shows that males are generally more active than females, with a lower median proportion spent in sedentary activity and higher proportions spent in the second half of light activity and higher. These differences become more pronounced at age 14, but for both sexes median sedentary time has increased and light to vigorous activity median time have decreased.

4. Methods

The scalar response fat mass at age 12 and 14 years is regressed onto a number of predictors. The response y_i is total fat mass for individual i, the vector x_i is the accelerometer profile for
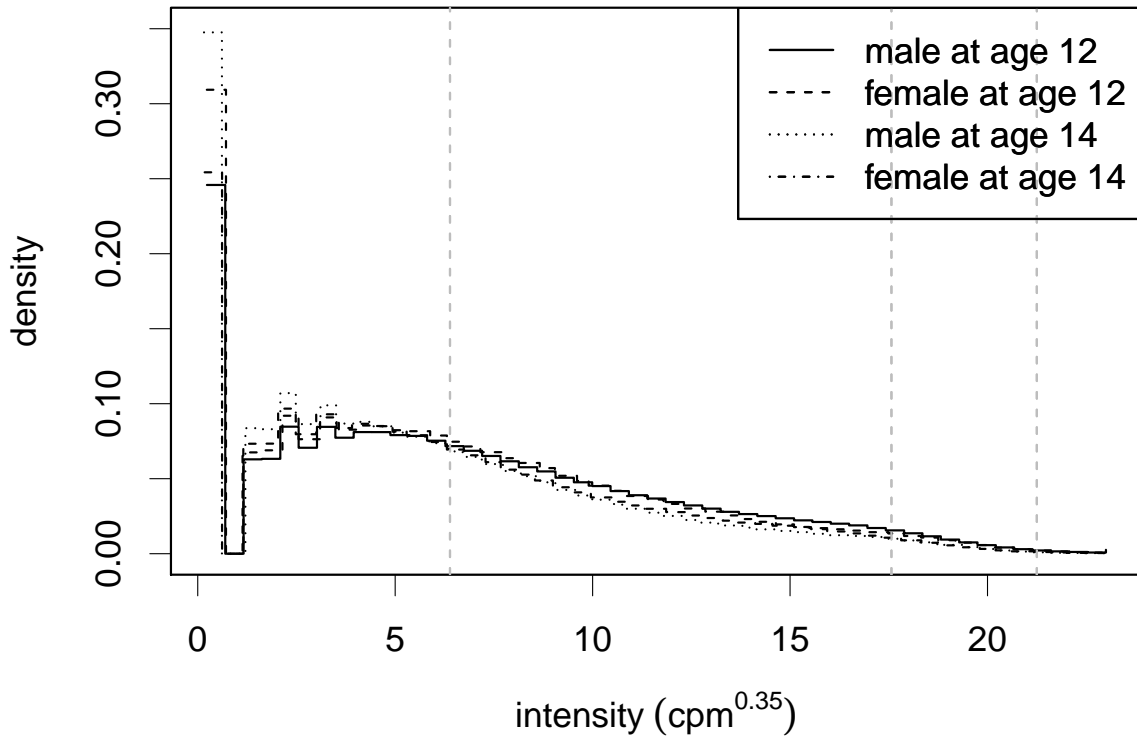
Figure 1. The median histogram of accelerometer profiles at ages 12 and 14 for males and females respectively. The density shown on the y axis is the relative frequency. The vertical lines denote from left to right the currently used cut points for light, moderate and vigorous physical activity at 200, 3600, 6200 counts per minute.

individual i, with 10080 entries and $z_i(x)$ is the corresponding histogram with 50 mid-points x_j, hence $z_i(x)$ is of length 50. We fit different variants of the following model:

$$log(y_i) = \alpha + \sum_j f(x_j)z_i(x_j) + \sum_l \gamma_l \texttt{confounder}_{li} + \delta \texttt{weartime}_i + \epsilon_i \quad (1)$$

where α is the intercept, the error ϵ_i follows a normal distribution with zero mean and variance σ^2 and the confounders are `sex`, `height (m)`, `height`^{2} and mean daily `weartime` (h). The $f(x)$ is an unknown smooth function to be estimated, which we represent with an adaptive smoother (Wood, 2006). The main difference to the usual linear regression model is that in addition to scalar predictors, sex, height, height^2 and weartime, there is also a functional predictor $\sum_j f(x_j)z_i(x_j)$ and the predictor function is a histogram. This type of model is also called a generalised regression of scalars on functions (Ramsay and Silverman, 2005). In the model term involving the histogram each bin has a weight $f(x_j)$, and the weights are constrained to vary smoothly over the range of the accelerometer counts. The $f(x_j)$ can be interpreted as the contribution of the histogram bar with midpoint x_j towards fat mass. We fit three variants of model 1: (1a) fat mass, confounders, weartime and physical activity at age 12; (1b) fat mass, confounders and weartime at age 14 and physical activity at age 12; (1c) fat mass, confounders, weartime and physical activity at age 14. There is no evidence

for different functions $f(x_j)$ for males and females as replacing the function $f(x_j)$ by two separate functions for males and females shows no significant improvement of goodness of fit.

We compare by χ^2 test the variants of 1a, 1b and 1c with simpler versions 2a to 2c, where the term involving the histogram of physical activity is replaced with MVPA whilst keeping all other terms the same:

$$log(y_i) = \alpha + \beta\mathtt{MVPA}_i + \sum_l \gamma_l\mathtt{confounder}_{li} + \delta\mathtt{weartime}_i + \epsilon_i \qquad (2)$$

Ranking the effects in terms of how much variation in fat mass they explain was assessed by dropping each term individually at a time while keeping all other terms in the model and performing an F test (analysis of variance).

5. Results

The results show that physical activity and sex are the most important factors for explaining variation in fat mass, when regressing physical activity onto fat mass at age 12 (model 1a/2a) the effect of physical activity is more important than sex, this order is reversed for the models with fat mass at age 14 (1b and 1c, 2b and 2c), with sex being more important than fat mass.

The histogram models 1a to 1c are superior compared to the simpler variants 2a to 2c in terms of goodness of fit, with a p-value below 0.00001 in a χ^2 test for the comparisons 1a vs 2a, 1b vs 2b and 3a vs 3b respectively. Also, the coefficients of variation for the histogram models are higher than for the simpler variants: 1a) R^2 = 0.292, 1b) 0.263, 1c) 0.258 compared to 2a) R^2 = 0.267, 2b) 0.248, 2c) 0.230 (see also Table 2 below). Figure 2 shows that the estimated weights $f(x_j)$ are positive in the range of the accelerometer profile which has a positive contribution to fat mass and negative in the range of accelerometer counts with a negative contribution to fat mass. For models 1a (fat mass and physical activity at age 12) and 1c (fat mass at age 14 and physical activity at age 12) the estimated weight function changes from positive to negative at around 3600 cpm the moderate activity cut-point as determined in the calibration study using a subset of the ALSPAC participants (Mattocks et al., 2007). For model 1b, with fat mass at age 14 and physical activity at age 12 the change from positive to negative is lower, at around 2756 cpm. Otherwise the estimated $f(x_j)$ is similar for all three models. The confidence intervals are wider for models 1a and 1c than for model 1b. The results indicate that the proportion of time spent in moderate and vigorous activity has a negative contribution towards fat mass and that the time spent in sedentary and the lower end of light activity has a positive contribution towards fat mass. Comparing the remaining estimates concerning sex, height and weartime between variants of model 1 and model 2 in Table 2 shows that estimates are very similar and results are as expected.
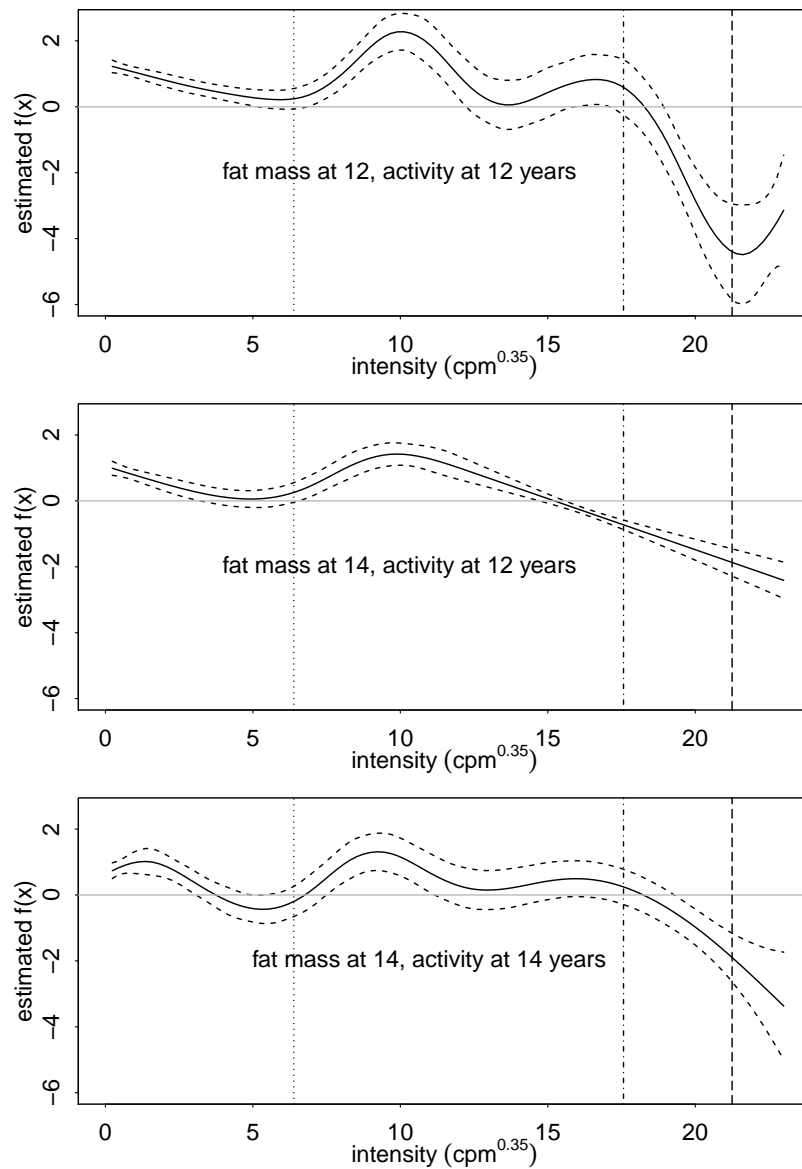
Figure 2. Estimated function $f(x_j)$ with 95% confidence bands for the three models fitted for models 1a - 1c. The vertical lines correspond from left to right to currently used cutpoints for light, moderate and vigorous physical activity at 200, 3600 and 6200 counts per minute. In model 1 the term involving the histogram each bin has a weight $f(x_j)$, and the weights are constrained to vary smoothly over the range of the accelerometer counts. The $f(x_j)$ can be interpreted as the contribution of the histogram bar with midpoint x_j towards fat mass.

6. Conclusions and discussion

Our new approach shows that the histogram is useful for exploring the whole range of the distribution of counts per minute when modelling fat mass without having to make any assumptions on cut-points. The proposed models perform better than models just incorporating MVPA as a predictor in terms of goodness of fit with the additional benefit of not requiring cut-points and giving additional insight. Physical activity and sex are the

Table 2. Model results for histogram models 1a to 1c and the simpler variants 2a - 2c. Parameter estimates are given with standard errors in brackets, coefficients of variation R^2 and sample size N are also stated.

	$\hat{\alpha}$	MVPA $\hat{\beta}$	sex male $\hat{\gamma}_1$	height $\hat{\gamma}_2$	height^2 $\hat{\gamma}_3$	weartime $\hat{\delta}$	R^2	N
1a	-16.80	na	-0.1650	19.70	-5.46	0.000370	0.292	4160
	(2.12)	na	(0.0162)	(2.79)	(0.92)	(0.000157)	na	na
2a	-15.00	-0.008100	-0.1570	19.80	-5.51	0.000446	0.267	4160
	(2.16)	(0.000520)	(0.0160)	(2.84)	(0.94)	(0.000159)	na	na
1b	-9.17	na	-0.4680	11.20	-3.01	0.000647	0.263	2400
	(3.19)	na	(0.0228)	(3.89)	(1.19)	(0.000225)	na	na
2b	-7.41	-0.007310	-0.4640	10.60	-2.84	0.000656	0.248	2400
	(3.22)	(0.000737)	(0.0226)	(3.93)	(1.20)	(0.000227)	na	na
1c	-7.17	na	-0.4710	9.52	-2.53	0.000230	0.258	2410
	(3.19)	na	(0.0227)	(3.90)	(1.19)	(0.000190)	na	na
2c	-6.71	-0.004120	-0.4940	10.20	-2.72	0.000104	0.230	2410
	(3.25)	(0.000632)	(0.0224)	(3.97)	(1.21)	(0.000190)	na	na

most important factors for explaining variation in fat mass, at age 12 (model 1a/2a) the effect of physical activity is more important than sex, this order is reversed for the models with fat mass at age 14 with sex being more important than fat mass. There were significant positive associations between fat mass and physical activity at different sedentary activity and lower light intensity levels as the 95% confidence bands of $f(z_j)$ did not include zero at these intensity levels. We found significantly negative associations with fat at moderate and vigorous activity levels (Figure 2). Although these results do not imply causality as our data are observational, the following statement is plausible: the time spent in moderate and vigorous activity has a negative contribution towards fat mass and the time spent in sedentary and very light activity (at around 700 cpm, corresponding to slow walking and similar activities) has a positive contribution towards fat mass. In ALSPAC physical activity levels were measured for a relatively short time, a minimum of three days and we assume that the measurements reflect the individuals typical activity pattern. There are some exceptions, as water based activities cannot be measured by the accelerometers used and some activities such as cycling are not well measured. Given the large sample size, we assume that these exceptions are negligible. Although typical densities at high intensity levels are low, the time spent at the most intense levels of activity is very important. The estimates of $f(x_j)$ are negative and have overall the highest absolute values in that range, implying that spending a certain number of minutes at the most intensive range of activity is associated with the highest reduction of fat mass. This has implications regarding the effectiveness of public health interventions, for example state provided after school activities with high levels of moderate to vigorous physical activity may be more effective for maintaining a healthy weight in adolescents than promoting walk to school.

Our method allows to consider the entire distribution of accelerometer counts in the model

without any of the collinearity problems introduced when summaries of specific activity levels are used simultaneously in the model. Using the summary total activity, defined as mean daily cpm, is equivalent to assuming a linear effect over the activity range. Using MVPA assumes zero effect of activity for an intensity below moderate and a constant effect of activity at and above the assumed cut-point for moderate intensity. Figure 2 clearly shows that the effect of physical activity is not linear and not constant over the activity range. Hence we can use our methodology as a diagnostic tool to evaluate whether specific single summary statistics for physical activity are appropriate as predictors for a specific health outcome.

The model results are robust to changing the number of bins of the histogram or using different transformations of accelerometer counts. We also find that changes in the data processing protocol concerning the block-zeros for defining non-wear time (10 minutes versus 60 minutes) make very little difference to our results.

Not much is known about temporal patterns of physical activity, e.g. activity levels across the day, and their relationship to health outcomes. Our method has potential to be useful for exploring such patterns. Applying our approach to other outcomes would also be of interest, since the association between physical activity and outcome may vary depending on the outcome. We might expect to see different effects for blood pressure (Leary et al., 2008) or depression (Wiles et al., 2012). We also expect that our approach will be useful to apply to other data of similar nature, e.g. long time series of data produced by monitoring individuals, arising in many medical and epidemiological areas.

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