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Predicting Runners' Oxygen Consumption on Flat Terrain using Accelerometer Data

KTH Bachelor Thesis Report

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Abstract

This project aimed to use accelerometer data and KPIs to predict the oxygen consumption of runners' during exercises on flat terrain. Based on many studies researching the relationship between oxygen consumption and running economy and a small set of data, a model was constructed which had a prediction accuracy of 81.1% on one individual. Problems encountered during the research include issues with comparing data from different systems, model nonlinearity and data noise. These problems were solved using transformation of data in the R software, model re-specification and identifying outlying observations that could be viewed as noise. The results from this project should be seen as a proof of concept for further studies, showing that it is possible to predict oxygen consumption using a set of accelerometer data and KPIs. With a larger sample set this model can be validated and furthermore implemented in Racefox's current service as a calibration method of individual results and an early warning system to avoid running economy deficiency.

Keywords

Bachelor Thesis, Predicting oxygen consumption, Accelerometer, Fitness technology

Sammanfattning

Prediktera löpares syrekonsumtion på platt terräng genom accelerometerdata

Detta projekts målsättning var att använda accelerometerdata och KPI-värden för att prediktera syrekonsumtion för löpare på plan mark. Baserat på ett urval av studier om korrelationen mellan syrekonsumtion och löpekonomi samt en liten mängd data så konstruerades en modell med en förklaringsgrad på 81.1% på en individ. Svårigheter under arbetet inkluderar datajämförelser, icke-linjäriteter och databrus. Detta hanterades genom datatransformationer i mjukvaran R, modell-modifikationer och identifikation av avvikande data som kunde klassificeras som brus. Resultaten kan ses som en förstudie som indikerar att det är möjligt att prediktera syrekonsumtion genom accelerometerdata och KPI-värden. En fortsatt större studie med fler individer och mätningar som underlag kan validera denna slutsats samt då implementeras i Racefoxs nuvarande tjänst som en kalibreringsmetod för individuella resultat och som ett varningssystem för att undvika försämrad löpekonomi.

Nyckelord

Kandidatexamensarbete, Prediktion av syrekonsumtion, Accelerometer, Träningselektronik

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1 Introduction

1.1 Background

1.1.1 History of Running

We are born to run. Running is believed to have evolved approximately 4.5 million years ago out of the early ancestor of humans that could walk upright on two legs (Chen 2006). The prevailing evolutionary theory is that the practice of persistence hunting of animals was a successful hunting technique that developed early humans' as endurance runners (Sears 2018; Carrier et al. 1984). Cognitive abilities and emotions are largely the same today as for humans beings living thousands of years ago, however our lifestyle has changed dramatically. Today we no longer run to survive but fact is that our brain functions best if we live a bit more like our ancestors did with more active lifestyles (Hansen 2016, pp. 12-13).

1.1.2 Health and Running

Modern brain research shows that physical exercise has immense positive effects on the brain, such as increased stress resilience, well-being, memory and intelligence (Hansen 2016, pp. 103-134). Running is an effective form of exercise and has been described as one of the world's most accessible sports. Due to its importance and popularity the field running economy has developed which describes efficiency of running. There is still a debate between leading actors in the running technology industry on how to model and estimate running efficiency and the results vary significantly. An important aspect is that running styles, body compositions and lengths are very individual. Thus implying the fact that to be able to answer the question of what is the most efficient way of running the individual has to be considered, and the real question to be answered is what is the most efficient way of running for this person.

1.1.3 Racefox - Running Technology Company

Racefox is a company trying to individualise running performance assessment by collecting and analysing individuals running measurements. There are many actors in the running technology industry with different kind of products and services. Significant for Racefox is that the technology is a sensor, called accelerometer, placed on the chest (as it is center of gravity) which in real time sends feedback to connected mobile phone with the Racefox application. After running sessions running economy and performance measurements are presented and explained. Furthermore there is a “digital coach” which communicates during the running session indicating progress in relation to set goal and also a dynamic training program that adapts training sessions after the individual’s development and ambition.

Today the models which measure running efficiency are built on maximal heart rate, which in turn is based on assumptions. Specifically, age combined with an assumed normal distribution on which heart rate target zone each runner should belong to. This means that for a majority of customers the heart rate zones will be correct but for some they might be somewhat off. Racefox strives to further individualise performance measurements by basing calculations on the measurement oxygen consumption. If you are able to cross reference the question of running efficiency with two different models the end result will increase greatly in precision. This thesis will investigate if it is possible and if so, how to predict runners oxygen consumption given earlier conditions.

1.2 Report Structure

The thesis consists of two separate parts. Part one examines the technical question at hand with a quantitative analysis. Part two discusses the business aspect of the company’s product and potential economical impact of part one.

1.3 Purpose

This project aims to find a way to predict runners oxygen consumption on flat terrain through multilinear regression using data from an accelerometer and corresponding key performance indicators provided by Racefox's algorithms. This can be implemented in Racefox's current running models, improving the general precision and increasing individual running technique forecasting. Customers running sessions will thus be more effective, safe and health beneficial.

The second part seeks to examine how this potentially could improve Racefox's current running analytics and furthermore investigate the company's opportunity to establish itself on the running technology market.

1.4 Research Questions

The scope of this report is set to answer the following questions.

1. Is it possible through multiple linear regression to predict runners oxygen consumption on flat terrain using accelerometer data and corresponding measurements acquired through Racefox's algorithms. If so, how accurate are these predictions?
2. How can predictions of oxygen consumption improve Racefox's service and what business opportunities are possible?

1.5 Method

1. Understand how oxygen consumption and running are correlated by reading previous works in the field and to meet with experts that have different specialities within the broad field which is physiology, technology and health science.
2. Combine the whole spectra of aspects in order to distinguish relevant delimitations and regressors for predicting oxygen consumption with a multilinear regression approach.

3. Building a model with actual oxygen consumption data as reference provided by a joint test by Racefox and GIH.
4. Test this model on our collected Racefox data and examine performance.
5. Perform VO_2 -max test at run lab company Aktivitus and see how the model performs on this input.
6. Use power (and thus energy cost of running) measurements made from the device attached to the shoe of the company Stryd and use the power measurements to correlate with Racefox data.
7. Compare results from steps (3) (4) (5) (6) to find the optimal model.
8. Literature study on the running technology industry.
9. Investigate the impact of prediction of oxygen data on Racefox models.
10. Interview with Racefox Co-Founder and Chairman Christer Norström and Product Manager Running Bernhard Hirschauer about running analytics and the potential market strategy for Racefox.

Part I

Predicting oxygen consumption with multilinear regression

2 Theoretical Framework

2.1 Previous Work

There have been a lot of previous studies on oxygen consumption and running economy. Running economy is defined as the steady-state oxygen consumption (VO_2) required at a given submaximal velocity or as the energy requirement per unit of distance run (Saunders et al. 2004). The correlation between oxygen consumption and energy expenditure per unit of distance will be used in this project. VO_2 is defined as the oxygen consumption, and $\text{VO}_{2\text{-max}}$ is defined as the maximal oxygen consumption for a given individual.

One article researching whether factors affecting pattern of movement of the limbs (gait factors) and ground reaction forces are related to energy cost of running in elite Kenyan runners found no correlation between the energy cost of running and significant gait factors such as ground contact time, stride length and stride frequency (Santos-Concejero et al. 2016). The accelerometer to be used in this project will measure gait factors, and these results will be taken into account. On the other hand, (Halvorsen, Eriksson, and Gullstrand 2012) concluded that there was indeed an inverse relationship between step frequency and VO_2 , as well as a positive linear relationship between vertical displacement and VO_2 . However, the amount of information explained by the model (R^2 - value) was 7%, which is deemed as very low.

In addition to looking at gait factors, (Kyröläinen, Belli, and Komi 2000) studied how biomechanical factors affect running economy. No exclusive biomechanical parameters (such as knee extensions, angular displacements of the hip etc.) could be identified to explain running economy. However, it was found that oxygen consumption and energy expenditure increases linearly up to 5m/s, and being roughly linear 5-7m/s. Gender did not affect oxygen consumption and energy expenditure. Another study made by (Pampero et al. 1986) found that if the subject is running at an average speed of 3.45 ms^{-1} (within $\pm 0.14 \text{ ms}^{-1}$) the average energy consumption amounted to $3.73 \text{ Jkg}^{-1}\text{m}^{-1}$ which showed to be equivalent to an oxygen consumption of $178 \text{ mlO}_2\text{kg}^{-1}\text{m}^{-1}$. At speeds equal to 85% and 120% of

the average speed, the average energy consumption amounted to 3.73 and 3.78 $\text{Jkg}^{-1}\text{m}^{-1}$ (equivalent to 178 and 181 $\text{mlO}_2\text{kg}^{-1}\text{m}^{-1}$), respectively. These results, though quite old, will be thoroughly used in constructing a predictive model.

According to (Morgan, Martin, and S.Krahenbuhl 1989) running economy, defined as the steady-state VO_2 for a given velocity, has been shown to account for a large and significant proportion of variation in distance-running performance among runners roughly comparable in $\text{VO}_{2\text{max}}$. Despite this recognition, relatively little is known regarding the potpourri of physiological, environmental, structural and mechanical factors potentially associated with a lower aerobic demand of running. Research has indicated that at low to moderate work rates, the steady-state energy condition is attained in about 3 minutes. Trained individuals reach steady-state sooner than unfit subjects. Intraindividual variation in economy has been shown to vary between 2% to 11%. A number of studies have documented the effect of increased core temperature on VO_2 , suggested reasons of rise in VO_2 include increased energy requirement for peripheral circulation, increased sweat gland activity, hyperventilation and a decreased efficiency of energy metabolism. Data from other studies (Maron, Wagner, and Horvath 1977), which have shown a reduction in VO_2 during the latter portion of a prolonged run, also support the possibility of increased muscular efficiency with elevated muscle temperatures. Racefox has access to terrain conditions, elevation change and temperature which could be included as a possible regressor, although it is not in this project's scope.

Conducting a $\text{VO}_{2\text{max}}$ -test reflects the individual cardiorespiratory fitness (CRF) and endurance capacity in exercise performance (Scott K.Powers 2017). Mounting evidence has firmly established that low levels of CRF are associated with a high risk of cardiovascular disease and all-cause mortality (*Assessing Cardiorespiratory Fitness in Clinical Practice* 2019). Classifications of fitness level using $\text{VO}_{2\text{max}}$ in run labs typically follow the Cooper Institutes CRF test standards (*Cardiorespiratory Fitness Tests* 2019).

Female (values in ml/kg/min)

Age	Very Poor	Poor	Fair	Good	Excellent	Superior
13-19	< 25.0	25.0 – 30.9	31.0 – 34.9	35.0 – 38.9	39.0 – 41.9	> 41.9
20-29	< 23.6	23.6 – 28.9	29.0 – 32.9	33.0 – 36.9	37.0 – 41.0	> 41.0
30-39	< 22.8	22.8 – 26.9	27.0 – 31.4	31.5 – 35.6	35.7 – 40.0	> 40.0
40-49	< 21.0	21.0 – 24.4	24.5 – 28.9	29.0 – 32.8	32.9 – 36.9	> 36.9
50-59	< 20.2	20.2 – 22.7	22.8 – 26.9	27.0 – 31.4	31.5 – 35.7	> 35.7
60 +	< 17.5	17.5 – 20.1	20.2 – 24.4	24.5 – 30.2	30.3 – 31.4	> 31.4

Male (values in ml/kg/min)

Age	Very Poor	Poor	Fair	Good	Excellent	Superior
13-19	< 35.0	35.0 – 38.3	38.4 – 45.1	45.2 – 50.9	51.0 – 55.9	> 55.9
20-29	< 33.0	33.0 – 36.4	36.5 – 42.4	42.5 – 46.4	46.5 – 52.4	> 52.4
30-39	< 31.5	31.5 – 35.4	35.5 – 40.9	41.0 – 44.9	45.0 – 49.4	> 49.4
40-49	< 30.2	30.2 – 33.5	33.6 – 38.9	39.0 – 43.7	43.8 – 48.0	> 48.0
50-59	< 26.1	26.1 – 30.9	31.0 – 35.7	35.8 – 40.9	41.0 – 45.3	> 45.3
60+	< 20.5	20.5 – 26.0	26.1 – 32.2	32.3 – 36.4	36.5 – 44.2	> 44.2

Figure 2.1: VO_2 max fitness classification

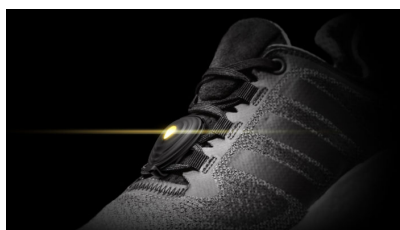
2.2 Running technology

EU innovation program Horizon 2020 stated that "Racefox will disrupt the personal coaching market by introducing a high-quality, low-price digital AI coach" and granted the company €1.85M (*European Commission Innovation program* 2019). The technology behind this digital AI coach consists of an accelerometer worn around the chest which in real-time downloads data via bluetooth to a connected mobile phone with the Racefox application.

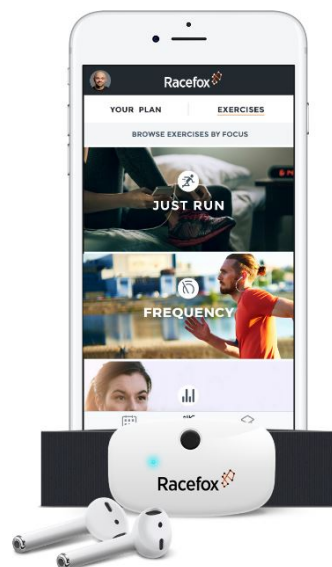
The mobile phone uses GPS to measure traveled path, distance and elevation. The accelerometer measures acceleration, vertical oscillation and heart beat frequency as raw data. Racefox furthermore calculate or model a number of running key performance indicators (KPI) that are used for assessing the customers running ability and improvement potential. Such as ground contact time (GCT) which is how many milliseconds the foot has ground contact during a running cycle, impact which is force that get excerpt during push off in a running step, drag which is the reduction in speed backwards with every step and bounce which is vertical oscillation while running. With Racefox there is direct feedback regarding unbalanced strides in combination with information concerning every training session (*Racefox Run* 2019). This is especially effective for endurance runners

as data is collected the entire session, so changes in running style when tiring is analysed.

Another company producing running technology is Stryd. Stryd produces a chiplike sensor attached to the shoe that similarly downloads data in real time to a bluetooth connected mobile phone with the Stryd application. A significant difference is that Stryd measure KPIs from the runners feet movement and which enables the sensor to measure the power of each step in terms of watts. Watts can in turn be converted into Joules, which as previously stated was correlated with oxygen consumption. One thing to keep in mind is that the Stryd only measures the mechanical effect, and thus the mechanical energy consumption. A Stryd chip will be used in this project and the data that Stryd provides will be used to correlate with the Racefox data and see whether there is a correlation between Racefox's KPIs and the power in each step.



(a) Stryd chip



(b) Racefox sensor

Figure 2.2: *Example of a Stryd chip and a Racefox sensor.*

2.3 Multiple Linear Regression Analysis

2.3.1 Mathematical Assumptions

Building a model based on multiple regression analysis is only half the work. In order to actually be able to use the model, it should conform to the assumptions of linear regression (Montgomery, Peck, and Vining 2012, p. 129). The assumptions are as follows:

1. The relationship between the responses and the regressors is approximately linear.
2. The error term has a mean of zero.
3. The error term has a constant variance.
4. The errors are uncorrelated.
5. The errors are normally distributed.

Assumptions 4 and 5 imply that the errors are random variables. These are the assumptions the model will be validated after and every assumption will be examined using different methods which will be presented further down. If assumption 4 is not fulfilled, the case of heteroscedasticity is implied, meaning that the variance does not vary as modeled.

2.3.2 Ordinary Least Squares

The model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \quad (1)$$

where

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nk} \end{bmatrix}, \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, \boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix},$$

is called a multiple linear regression model with k *regressors*. In general, \mathbf{y} is an $n \times 1$ vector of the observations, \mathbf{X} is a $n \times k$ matrix of the levels of the regressor variables, β is a $p \times 1$ vector of the regressors and ϵ is an $n \times 1$ vector of the random errors (Montgomery, Peck, and Vining 2012, p. 72). This is the model which will be used in this project, with the goal to estimate the best regressors and choose which are the most relevant. Estimation of regressors will be done using the method of least squares.

The method is to find the vector $\hat{\beta}$ which minimizes the sum of squares, which can be expressed as:

$$\mathbf{S}(\beta) = \sum_{i=1}^n \epsilon_i^2 = (\mathbf{y} - \mathbf{X}\beta)'(\mathbf{y} - \mathbf{X}\beta). \quad (2)$$

To find the minimizing vector, the expression must be derived. By doing this, the least-squares normal equations are obtained:

$$\mathbf{X}'\mathbf{X}\hat{\beta} = \mathbf{X}'\mathbf{y}. \quad (3)$$

Thus, this yields the least-squares estimator

$$\hat{\beta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}, \quad (4)$$

which will be used when estimating the regressors. From this estimator, the fitted values \hat{y} will be produced.

2.3.3 Multicollinearity

To confirm whether the model will perform adequately, the level of linearity must be examined between the regressors to choose the most independent set of regressors. For this, several multicollinearity diagnostics will be used.

1. The correlation matrix between the regressors will be examined, which is defined as $\mathbf{X}'\mathbf{X}$ (Montgomery, Peck, and Vining 2012, p. 294) and the off-diagonal elements of this matrix describe the level of correlation between the regressors. This diagnostic is limited since it only compares pairs of regressors.

2. The diagonal elements of the matrix

$$\mathbf{C} = (\mathbf{X}'\mathbf{X})^{-1}$$

are called Variance Inflation Factors (VIF) and will be used to detect multicollinearity. The diagonal elements of \mathbf{C} , C_{jj} can be expressed as $C_{jj} = (1 - R_j^2)^{-1}$, (Montgomery, Peck, and Vining 2012, p. 296) where R_j^2 is the coefficient of determination obtained when x_j is regressed on the remaining $p-1$ regressors. From this follows the Variance Inflation Factor formula for regressor j :

$$VIF_j = C_{jj} = (1 - R_j^2)^{-1}, \quad (5)$$

which will be used. When the VIF -values are above 10, there is an issue with multicollinearity. (Kutner, Nachtsheim, and Dr. 2004).

To treat issues with multicollinearity, various instances of model respecification will be performed.

2.3.4 Data Diagnostics

The data which is recieved from the different systems will be diagnosed to treat data points which differ from the majority, also called outliers. These can be divided into two categories:

1. Leverage points. These points lie almost on the regression line passing through the rest of the sample points, but with an unusual x -value.
2. Influential points. These points have unusual x and y -values and do not lie on the regression line. Thus the regression line is tilted towards them - having a noticeable impact on the model coefficients.

Leverage points do not affect the regression coefficients that much unless their residual from the regression line is high - which makes them influential points. Therefore only influential points will be diagnosed by using two measures of influence: *DFFITs* and *COVRATIO*.

DFFITS is defined as:

$$DFFITS_i = \frac{\hat{y}_i - \hat{y}_{(i)}}{\sqrt{S_{(i)}^2 h_{ii}}}, \quad (6)$$

where $\hat{y}_{(i)}$ is the fitted value of \hat{y}_i without the use of the i :th observation and h_{ii} is the amount of leverage produced by the i :th observation on \hat{y}_i . It is a measure of how many standard deviations the fitted value y_i changes if the i :th observation is removed (Montgomery, Peck, and Vining 2012, pp. 212-218). All observations where $|DFFITS_i| > 2\sqrt{p/n}$ will be examined.

COVRATIO is defined as:

$$COVRATIO_i = \frac{(S_{(i)}^2)^p}{MS_{Res}^p} \left(\frac{1}{1 - h_{ii}} \right), \quad (7)$$

and express the role of the i :th observation on the precision of the observation (Montgomery, Peck, and Vining 2012, p. 219). Any observation which $COVRATIO_i$ exceeds the interval of $1 \pm 3p/n$ will be examined.

Observations exceeding both the accepted interval for *DFFITS* and for *COVRATIO* will be tended to.

2.4 Time Series

Since the data comes from the progression of a runners track, it follows a time sequence (with other words called a time series). Time is an important parameter and the time since the start of the track in seconds will be taken into account as a regressor in the linear model.

2.5 Variable Selection and Model Validation

2.5.1 Forward Selection & Backward Elimination

To further improve the resulting models, selecting which variables are important and which are redundant is necessary. The methods that will be used for this purpose are the following:

1. **Forward Selection.** This procedure begins with the assumption that there are no regressors in our model other than the intercept. An effort is made to find the optimal subset of regressors by inserting them one at a time. The first regressor to be entered is the one with the largest simple correlation with the response variable y . This is also the regressor that will produce the largest value of the F-statistic for testing significance of regression. This regressor is entered if the F-statistic exceeds a preselected F-value, F-to-enter. The second regressor chosen for entry is the one that now has the largest correlation with y after adjusting for the effect of the first regressor entered on y (Montgomery, Peck, and Vining 2012, p. 345), and so on.
2. **Backward Elimination.** This procedure begins with the full model with all candidate regressors. Then the partial F-statistic is calculated for each regressor as if it were the last one to enter the model. The smallest of these statistics is compared to the preselected F-to-exit value and if it is less than the exit-value then this regressor is removed. After this, the new model is fit and the F-statistic is recalculated for each remaining regressor and the procedure repeats (Montgomery, Peck, and Vining 2012, p. 347).

The model which has the lowest C_p -value will be chosen from these procedures.

2.5.2 Mallows's C_p and Adjusted R^2

As a deciding factor for which model performs the best, the Mallows's C_p -value will be used. The Mallows's C_p is defined as:

$$C_p = \frac{SS_{Res}(p)}{\hat{\sigma}^2} - n + 2p, \quad (8)$$

where $\hat{\sigma}$ is the estimate of the variance in the error terms. A low Mallows's C_p is desirable, and therefore the model with the lowest value will be chosen (Montgomery, Peck, and Vining 2012, p. 334). A low Mallows's C_p -value is approximately the amount of regressors in the model (Gilmour 1996).

To confirm the explanatory skills of the model, a variant of the coefficient of

multiple determination (R^2) will be used. The R^2 -value is a measure of how much of the response is described by the regressors in the model. The adjusted R^2 -value takes into account the significance of the variables in the model as well, and is defined as:

$$R_{adj}^2 = 1 - \frac{n-1}{n-p}(1 - R^2). \quad (9)$$

A high value on the adjusted R^2 -value is desirable, which is what will be used as a measure of the models precision.

2.5.3 Cross-Validation

K-fold Cross-Validation will be used to validate the model chosen. The method splits the data set into K subsets (folds) of approximately equal size. Then the model is trained on K-1 folds, and tested on the K:th fold. This is repeated K times for each fold (Kohavi 1995). After this procedure is done, the fitted values \hat{y}_i are compared with the fitted values from the K-fold Cross-Validation. With this, a mean residual sum of squares between these is calculated, which is desired to be low since that indicates that the model performs well on all folds. The K will be chosen to 10, since that number have been empirically shown to work well (Kuhn and Johnson 2013, p. 70).

3 Methodology

3.1 Limitations and Delimitations

3.1.1 Type of Terrain

Running can be done on different terrains and gradients, each affecting a runners running economy differently (Prampero 2015, p. 110). Thus, prediction of oxygen consumption is dependent on what terrain the track consists of. By recommendation of a researcher in environmental physiology at KTH, only tracks that have been conducted on flat terrain will be studied to be able to manage complexity. This was instructed to the wearers of the Racefox sensors which were received for this project. Racefox define elevation change gradient of positive 2.5% or more as uphill and negative 2.5% or less as downhill, thus defining flat terrain as elevation change gradient kept between -2.5 and 2.5%.

3.1.2 Factors Affecting Running Economy

Age, lifestyle and running skill are factors that effect oxygen consumption according to (Martin, Rothstein, and Larish 1992). Receiving only four sensors the amount of test subjects was limited and thus the diversity amongst the subjects is limited. The studies conducted by (Pampero et al. 1986) whose results are going to be used in the model creation were conducted on male runners. To better apply the results on the data received from the Racefox sensors, only male runners with approximately the same level of running skill received a sensor. The age is though diverse, ranging from 21 to 54 years.

3.2 Data Collection

For the collection of raw data from Racefox, four Racefox sensors were borrowed for the project. The sensors were given to four subjects, with approximately the same level of skill and physical activeness. They differed mainly in age and length.

Table 3.1: Table of subjects

Subject nr.	Age	Weight	Length	Gender
1	23 years	84 kg	189 cm	Male
2	43 years	68 kg	175 cm	Male
3	21 years	69 kg	183 cm	Male
4	54 years	67 kg	180 cm	Male

To receive the data, inquiries were made to Racefox to receive the raw data files. The files contained time-based data with 26 different KPIs. According to Racefox's CTO, only 16 of them are expected to have an impact on oxygen consumption and all are measurements of physical movements.

Table 3.2: Table of Racefox KPI's

KPI	Explanation	Unit
GCT	Ground Contact Time	$10^{-3}s$
VO	Vertical Oscillation	$10^{-2}m$
SPM	Steps per Minute	$stepsm^{-1}$
rFootsym	Right foot symmetry	N/A
lFootsym	Left foot symmetry	N/A
diffFootsym	Difference in foot symmetry	N/A
landingDrag	The reduction in speed backwards with every step	ms^{-1}
maxY	Maximal acceleration in Y-axis	ms^{-2}
acc_x	Acceleration in X-axis (left)	ms^{-2}
acc_y	Acceleration in Y-axis (up)	ms^{-2}
acc_z	Acceleration in Z-axis (forward)	ms^{-2}
HR	Heart Rate	bpm
Distance	Distance run	m
Speed	Distance covered by unit time	ms^{-1}
Elevation	Elevation above sea level	m
t	Time since start	s

Thus these are the variables that will be used in building the model for predicting oxygen consumption.

Racefox had already made some experiments with the accelerometer and oxygen masks together with the Swedisch School of Sports and Health Science (GIH). For that experiment, three subjects ran on three different types of terrain (whereas one of them was asphalt) with the accelerometers and masks that measured oxygen consumption. The different terrains were passed during the same track. The results from this experiment will be used to build a model, since the responses

(VO₂) are in the data set and were received for the sake of this project.

Subject 1 also received a Stryd-chip to put on the shoe. Stryd allows their time-based raw data files to be downloaded directly without having to inquire about it. The subject ran with the Racefox-sensor and Stryd activated at the same time which allowed collection of data from both systems during the same track.

Together with the Racefox sensor and Stryd-chip, subject 1 was allowed to conduct a VO₂-test on a treadmill, where the oxygen consumption was measured every breath. The raw data from this test was then received and was used as a testing data set for two of the models.

3.3 Transcript of Data

3.3.1 Data from Different Systems

The data used in the models came from three different systems: Racefox, oxygen masks and Stryd which all are based on different time sequences. The oxygen masks time sequence is the interval of a breathing cycle (approximately 2-3 seconds), Stryds sequence is every second and Racefox's sequence is every step-cycle (approximately 0.4 seconds).

To be able to compare the data sets it was necessary to transcribe the data to the same time sequence. This was done using R software. To compare the Racefox and oxygen mask data, the data was aggregated into 5-second intervals and all values within the intervals were averaged and merged together. This data set was then used to build a model using the VO₂-responses from the oxygen masks. Since the different terrains were passed during the same track, the data points which would serve as the starting and ending points of each terrain were chosen manually. In this case the data from Racefox did not contain the raw accelerometer data, nor did it contain the weight of the subjects.

To compare the Racefox data with the Stryd, the Racefox data was aggregated into 1-second intervals and all values were averaged and merged together with the Stryd data. This data set was then used to build a model using the Watt-measurements from the Stryd system. There was also a difference in when the

systems were turned off. Stryd was the first system to be turned off, the length of the track was based solely on the Stryd system and all data points from Racefox which exceeded the time Stryd was turned on were removed.

The data from the VO_2 -test was also aggregated into 5-second intervals, together with the Racefox-data from that track. The Racefox data was then inserted into the models and the real VO_2 -observations were compared to the predicted ones.

3.4 Regression approach

3.4.1 Multilinear Regression Model

After the data was transcribed into comparable data sets and all necessary modifications were made, the model was ready to be built. Three models were created using the R software:

1. Model using data from the collaboration between GIH and Racefox. This data set contained 169 observations (after the aggregation of data) and the full model contained all variables in Table 3.1 except for acc_x , acc_y , acc_z , distance, speed and elevation. The excluded variables were not part of the data set received from Racefox.
2. Model using the results from (Pampero et al. 1986) and Racefox-data from the four subjects. This data was also aggregated into 5-seconds intervals to reduce the impact of the start and ending points, containing 4004 observations. After that, for each interval the average oxygen consumption was calculated using the formula $0.178 \text{ l O}_2\text{kg}^{-1}\text{km}^{-1}$. Since the weight and distance run was used to calculate the responses VO_2 , these variables were removed from the model. Thus the full model contained all variables described in Table 3.1 except for distance.
3. Model using the Stryd data and the Racefox data from the subject who ran with the Stryd. There were issues putting the Racefox belt so that it could measure the heart rate, which resulted in the first 403 observations showing a heart rate of 0. These were cut off, after which the data set contained 2604

observations. The full model used all variables described in Table 3.1 and the responses were the Watts for each step.

Common for all models was that the linearity assumption was tested using plots of the residuals and estimating whether they were symmetrically distributed along the zero-line. Influential observations were detected using built-in R code producing the relevant values and then forward selection was performed using built-in functions, followed by Cross-Validation.

If the linearity assumptions were not satisfied, several nonlinear combinations would be tried until yielding a satisfying result.

3.4.2 Variable Selection

Variable selection will be based on the forward selection or backward elimination algorithms, but due to the irregularities in the data and the human error, the results from the algorithms might therefore seem illogical. Therefore, the resulting models variables will be seen as a direction of which variables seem to have an impact on the oxygen consumption.

4 Results

4.1 Multilinear Regression Models

4.1.1 Model A: Racefox and GIH-model

This model based on the responses available showed no signs of nonlinearity by looking at the residuals. They are approximately symmetrically distributed along the zero-line, meaning that linearity assumptions between response and regressors seem to hold.

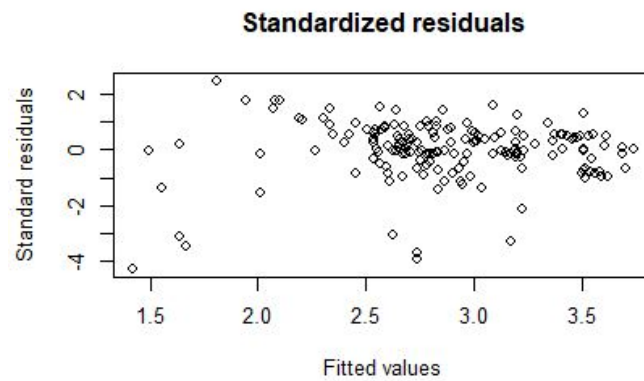


Figure 4.1: *The plot of residuals vs the fitted values*

In this data set, there were some outliers. The accepted intervals for the influence measures were calculated to:

$$I_{DFITS} = [0, 0.5133], I_{COVRATIO} = [0.802, 1.198]. \quad (10)$$

and there were three observations whose influence measures fell out of the accepted intervals. These observations coincided with the manually selected data

Table 4.1: Influential outliers

Observation	DFITS	COVRATIO
1	-4.71	0.56
80	-1.27	3.29
167	-2.19	0.69

points which served as start and ending points for the tracks. Therefore they were

removed from the data set.

The correlation matrix and VIF-values showed no issues with multicollinearity, meaning that there are no linear dependencies between the different regressors. This also means that the KPI's Racefox calculates are not based on each other and are independently evaluated.

Table 4.2: Table of VIF-values

Regressor	VIF	Regressor	VIF
GCT	2.37	diffFootsym	7.44
VO	1.47	landingDrag	1.40
SPM	1.31	maxY	2.49
rFootsym	4.06	HR	2.84
lFottsym	3.39	t	2.20

The forward selection algorithm was performed and yielded that the best model would contain the following regressors:

Table 4.3: Table of Regressors

Regressor	Value	95% Std. Error
Intercept	9.658	15.039
landingDrag	2.476	0.353
SPM	-0.040	0.005
GCT	0.100	0.039
HR	0.100	0.037
diffFootsym	6.804	1.453
t	0.008	0.005
maxY	-0.754	0.204

This resulting model had an R^2_{Adj} -value of 0.702 and a Mallows's C_p -value of 5.35. Mallows's C_p -value is deemed as low and this model explains 70.2% of the variation in the responses, which is also deemed as high.

4.1.2 Model B: Racefox and consumption assumptions-model

This model did not show any signs of nonlinearity after analysing the plot of the residuals, meaning that this model does not either contain any linear dependencies between regressors. Thus the linear assumptions seem to hold.

Some observations seem to be on a line with a negative slope. These will be discussed later.

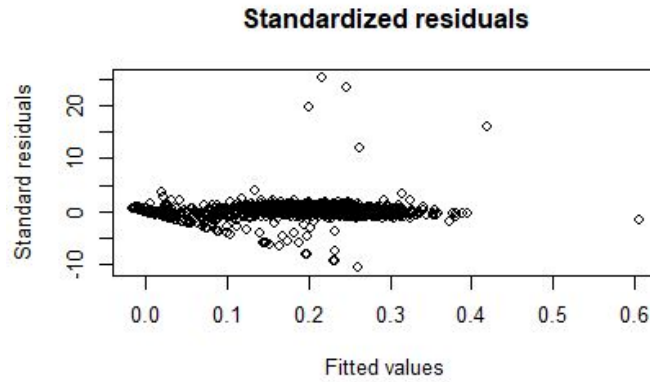


Figure 4.2: *The plot of residuals vs the fitted values*

The accepted intervals for the outliers influence measures were:

$$I_{DFFITS} = [0, 0.1267], I_{COVRATIO} = [0.988, 1.012]. \quad (11)$$

And there were no observations who fell out of the intervals in a way that could affect the models precision, mainly since the amount of observations was large and individual observations have a small impact.

The correlation matrix and VIF-values showed some issues with multicollinearity, meaning that there are some small linear dependencies between different regressors. LandingDrag and acc_z have an almost perfect negative linear relationship, which is reasonable since landingDrag is a measure of how much speed forward you lose with each step. Since this collinearity was seen as reasonable, no action was taken.

Forward selection algorithm was then performed and gave the following resulting regressors:

From these regressors, the resulting model had an R^2_{Adj} -value of 0.834 and a Mallows's C_p -value of -1.12. This value of Mallows's C_p is deemed as low. The model explains 83.4% of the variation in the responses, which is excellent.

Table 4.4: Table of VIF-values

Regressor	VIF	Regressor	VIF
GCT	3.65	maxY	11.86
VO	2.41	HR	1.34
SPM	1.42	speed	1.42
rFootsym	5.92	elevation	1.62
lFootsym	5.48	acc _x	2.64
diffFootsym	12.03	acc _y	3.46
landingDrag	21.13	acc _z	10.07
t	1.13		

Table 4.5: Table of Regressors

Regressor	Value	95% Std. Error
Intercept	-0.789	0.821
speed	10.852	0.091
GCT	-0.007	0.002
lFootsym	0.265	0.180
acc _z	0.079	0.064
VO	0.080	0.025
HR	0.003	0.003

4.1.3 Model C: Racefox and Stryd-model

This model did show signs of nonlinearity when analysing the plot of the residuals. The model tended to predict too low for higher values of Watts, thus prompting to try nonlinear combinations of the regressors.

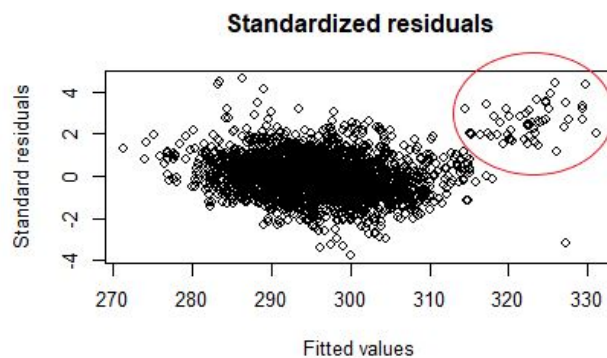


Figure 4.3: The plot of residuals vs the fitted values, with the under-predicted values within the red circle

Intervals for outlier influence measures were:

$$I_{DFFITS} = [0, 0.4311], I_{COVRATIO} = [0.861, 1.139]. \quad (12)$$

No observations fell out of both intervals, which meant that no individual observation was influential enough to have a significant impact on the model's precision.

To combat the issue of nonlinearity all tuples of the regressors were added to the model. The residual plots from the new model showed no more signs of wrongful prediction. Therefore, with these modifications, linearity assumptions were satisfied.

The cost of satisfying the linearity assumptions was the increased issue with multicollinearity. VIF-values ranged between 6.66 and 143240, which meant that issues with multicollinearity were high. The collinearity, however, is expected, since the majority of the regressors now consist of tuples of one another. Therefore, no action was taken to combat the multicollinearity.

The forward selection algorithm yielded a model consisting of 58 different regressors, which had an R^2_{Adj} -value of 0.490 and a Mallows's C_p -value of 9.15. This meant that 49% of the power was explained by Racefox KPI's and combinations of them. A high value, compared with the R^2_{Adj} -value of the linear model C which was 0.22.

4.2 Testing models on VO₂ data

To test the predictive power of the models, the VO₂-data and Racefox-data from the same track from subject 1 was inserted into the model A and B. The figure below shows the resulting VO₂ and HR measurements from the track.

Cardio-respiratory Fitness (ml/Kg/min)					
Rank: 96% Measured					
					54,6
Very Poor	Poor	Fair	Good	Excellent	Superior
< 37,1	37,1 - 41,0	41,0 - 44,2	44,2 - 48,2	48,2 - 54,0	> 54,0



Figure 4.4: The resulting VO_2 and HR from the test.

4.2.1 Predictive power of Model A

Inserting the testing data into model A and then comparing the predicted VO_2 with the real VO_2 by calculating the mean ratio between the predicted values and the real values yielded a model accuracy of 81.1%. This means that on average, the real and predicted values differed with 18.9%. The difference was confirmed by calculating the total oxygen consumption. Real oxygen consumption amounted to 14.1 litres of oxygen, while the predicted was 17.2 litres, which is an over-prediction of around 18%.

4.2.2 Predictive power of Model B

Performing the same procedure on this model and then calculating the ratio between predicted and real values yielded a model accuracy of 67.3%. Thus, on average, the real values and predicted values differed with 33.7%. This difference

was confirmed by calculating the total oxygen consumption. Predicted oxygen consumption amounted to 9.42 litres, while the real oxygen consumption was 14.1 litres. This is an under-prediction of around 33%.

5 Discussion

5.1 Interpretation and Impact

Examining the results show some interesting findings. It is possible to predict the oxygen consumption given the accelerometer data, with varying accuracy depending on the data the model is built on. If the model is built on data from real VO_2 -measurements, it is clear that it has a higher precision. Model A was built on 167 observations and yielded a prediction accuracy of 81.1%, while model B is built on 4004 observations and yielded an accuracy of just 67.3%. Thus, it requires much less observations to reach a higher accuracy if the data comes from real observations. It should also be kept in mind that model A did not contain the raw accelerometer data (acc_x , acc_y , acc_z), thus affecting the precision. If those variables could be evaluated together with the model, the resulting model might differ and perform even better.

There is also a seemingly linear relationship between VO_2 and the regressors, since the data did not show any signs of nonlinearity. This implies that it is not computationally difficult to predict VO_2 , and thus can be implemented quite easily in Racefox's applications and still provide accurate predictions.

Both models contained the regressors GCT, VO, HR, while differing on speed, Footsym, SPM, time since start and acceleration in the axis. GCT, VO and HR thus seem to be most influential when predicting VO_2 , but model B gave some odd results. One was that SPM and time since start was not part of the model, and only lFootsym was part (and not the other symmetries). This is probably due to the fact that model B is built solely on assumptions and the results from the selection algorithms yield the best mathematical result, which is not really tied to real life. To better compare whether the resulting regressors are reasonable, the same regressors should be in model A. Thus, the influential regressors are probably more than only GCT, VO and HR.

Data noise has been an issue in this project as well, possibly impacting the model's precision. Some times, the pulse belt hasn't been on properly on the subjects, yielding a HR of zero during some instances. Events such as stopping for a red

light or hastily getting out of the way of a bike result in outlying observations that need to be filtered. This was not done in this project, due to the complicated nature of those observations. A form of systematic noise is most probably the cause of the line of residuals with a negative slope in model B, where it might be one subject whose SPM perhaps affected the predictions linearly. These observations were not examined in this project since they were deemed to be too few.

Trying to predict the power from the Stryd-chip proved to be not as successful as predicting the oxygen consumption. There was a nonlinear relationship between the regressors and the power, which complicates the computation. Even after adding nonlinear combinations, the model had a R^2_{Adj} of 49%, which is low. Also, it is unclear how the forward selection algorithm is affected by the presence of nonlinear regressors. The predictive power could not be evaluated, since Stryd only measures the mechanical power and energy which cannot be entirely correlated with oxygen consumption where the total energy expenditure is required.

Thus, to measure the power and correlate it with oxygen consumption, other calculations of power should be done using other sensors than Stryd which measures the total energy expenditure and power.

5.2 Recommendations for further studies

This project should be viewed as a proof of concept conducted on a few individuals with relatively small amount of data. Recommendations for further studies are as follows:

1. Relevant KPIs for predicting oxygen consumption need to be distinguished. This project suggests that accelerations, landingDrag, VO, SPM, GCT and HR can be used for that purpose. To obtain a definite answer on which KPIs should be in the predictive model, more VO_2 -tests with Racefox sensors on flat terrain on a larger set of subjects should be conducted. This is because of the model built on real-life observation was superior to the model based on assumptions.

2. The new VO₂-tests should be conducted on a larger and more relevant set of subjects. This set should be a subset of Racefox's total customer-base and be as diverse as possible. Genders, ages, weights, lengths and running skill should be mixed to obtain as relevant observations as possible.
3. Steps of quality. Since running is uncontrolled and free to do any time, there will be noise in the data streams (such as stopping for a red light). This noise does not exist in a lab-environment where the VO₂ tests are conducted. Thus, this noise has to be filtered from the data streams by looking at anomalies in the accelerometer data and identifying which actions can be correlated with these anomalies.
4. On the new and filtered data, a model can be constructed using multilinear regression. If the data show no signs of nonlinearity, the model will be linear and thus computed easily in real-time.
5. To validate the model, the same set of subjects should conduct another VO₂-test which will be used as a testing set, to see how well this model performs.
6. If this model performs well on approximately flat terrain, calibrating the model for running on sloped terrain and other terrains by performing new tests prone to this type of terrain. This should be done if deemed of value, which depends on what terrain is most common amongst Racefox's customers.
7. After a model is validated, systems such as "early warning systems" and cross-referencing methods can be implemented to give individualised feedback.
8. Conduct further tests with power-measurements to try to predict the power from Racefox KPI's, which can serve as either a correlating factor with oxygen consumption or as its own, new KPI.

Part II

The market for running technology

6 Background

6.1 Previous studies regarding the market of running technology

Previous studies of the running technology consist of two parts. The first part investigates the products and technical specifications of the leading industry actors. The second part evaluates general customer behaviour regarding wearable technology.

Leading actors provide smart watches, sport watches, activity trackers, pulse straps, foot-and pod accelerator sensors. Garmin, Polar, Fitbit and Suunto are the largest companies in following order with aspect to number of employees and can be considered market dragons. These companies offer the entire range of products but with varying specifications, with Fitbit specialising within health solutions (*Sports technology guide* 2019). Racefox, Stryd and RunScribe are smaller more software oriented companies with core competence in movement pattern analysis(*Stryd* 2019)(*RunScribe* 2019)(*Racefox Run* 2019). Endomondo, Strava, TrainingPeaks, Nike Runners club are free social platforms that provide training planing and more basic training metrics (*TrainingPeaks Features* 2019)(*Endomondo* 2019)(*Strava Features* 2019)(*Nike Run Club* 2019).

The use of fitness technology has increased dramatically the past decade with the connected wearables becoming cheaper and more powerful. A study from PWC showed that Fitness wearables are the main reason for purchase of wearable technology with an increasing positivity to quantify training data which can translate into practical change that influences performance (*PWC: The wearable life 2.0* 2019). Tractica also forecasts an increase of the wearables devices until 2021, with total shipments for all wearable devices to 560 million in 2021, which means an estimated device revenue of \$95.3 billion in 2021 (*Forecasts on wearables* 2019). Its forecast projects sales of 310.4M wearable devices worldwide this year, generating a total of \$30.5BN in revenue — of which it expects \$9.3BN to come from the smartwatch category specifically. By 2021 Gartner estimates that sales of smartwatches will total nearly 81M units — representing 16% of total

wearable device sales (*Business Forecast wearable technology 2019*).

6.2 Running technology market

In broad terms three groups of companies exist within the running technology market. The first group are similar to Facebook but for runners. Companies like Runkeeper, Strava and Endomondo are large platforms with users world wide which core company value is to connect runners with friends and communities giving access to own and others exercises, training schedules and basic running analytics. Great for boosting motivation and keeping track of exercises.

The second group include gadget wearables and data-driven companies, for example Polar, Suunto, Garmin, Stryd and Racefox. These companies are technocratic and core company value is providing users with correct training data enabling its users to improve and gain insights with this knowledge. These companies are hardware and software-based to different degrees. Garmin and Polar are for example global actors which offers a wide range of different wearables and running analytics. Stryd and Racefox are smaller companies that provide one sensor to acquire data but primary are software-based companies with holistic data driven analytics and feedback as their unique selling point.

The third group are companies that offer health solutions, for example Fitbit (*Fitbit: Health Solutions 2019*). These companies do in fact provide basic running measurements and KPIs such as heart beat, distance and energy expenditure, but mainly focusing on other health and lifestyle related metrics such as sleep, activity and heart rate monitoring. Core company value is collecting, presenting and evaluating customers health and lifestyle related data.

6.3 Racefox's position

Racefox is a running technology company in the early stage of establishing itself in the market. It offers a holistic view on training providing a data collection and running/skiing analysis. Racefox is first and leading actor within the niche market for skiing analysis with an current expansion into the Norwegian market

underway. With training analysis meaning more in-depth data analysis and interpretation on how KPIs should be interpreted and utilised for the individual. Today Racefoxs core competence is the running analysis but the company offers a basic sensor that needs a mobile phone to process and collect the training data.

7 Methods

7.1 Literature studies

Initially the question of how values of oxygen consumption are utilized as a fitness level measurement was investigated, finding that VO_2max testing is the gold standard or most accurate test of aerobic or cardiovascular fitness(**Leaver**). Classifications of fitness level used in run labs usually follow the Cooper Institutes CRF test standards (*Cardiorespiratory Fitness Tests* 2019). Thereafter this functionality was investigated specifically for Racefoxs service and prerequisites by discussing the topic with with company employees.

7.2 Interviews with Racefox

Two semi-structured interviews were conducted with Racefox Chairman Christer Norström and Racefox Product Manager Running Bernhard Hirschauer. The meeting agenda contained the following questions:

1. How does the market for running technology look like and what is Racefox's position in it?
2. Important customer segments for Racefox.
3. What differentiates Racefox from competition.
4. Racefoxs short term aims.
5. Racefoxs long term ambitions and obstacles to achieve this.

7.3 Limitations and Delimitations

Findings in "Part II - The market for running technology" are based on two interviews with Racefox managers and to some degree subjective market research conducted by authors. The nature of the research questions being a case study on a specific company, namely a establishing start-up within running analytics, make conclusions company specific and are not necessarily generalisable. Different

applications and products were evaluated and diagnosed after publicly available information, such as number of customers, functionality and ratings. Therefore should results in this section serve as inspiration for further study and not as basis for decision making.

8 Theoretical Framework

8.1 Market Segmentation

Markets consist of buyers which can differ in their needs, resources, locations, buying attitudes and buying practices. Through market segmentation companies can divide large heterogeneous markets into smaller segments that can be reached more efficiently with products and services that match their unique needs (Phillip Kotler 2013). In this paper segmenting topics used for analysis are:

1. Geographic segmentation: Divides customers into segments based on geographical areas such as nations, states, regions and cities.
2. Behavioral segmentation: Division based on customers' attitude, response and use of a product.
3. Demographic segmentation: Divides customers into segments based on values such as for example age, gender, family, income and education.
4. Psychographic segmentation: Used as a supplement to geographic and demographic segmentation and divides people according to their attitudes, values, lifestyles, interest and opinions.

After defining market segments comes market targeting which involves evaluating each market segment's attractiveness and selecting one or more segments to enter. A company should target segments in which it has a differential advantage over its competitors; where it can generate the greatest customer value and sustain it over time (Phillip Kotler 2013).

8.2 SWOT-analysis

SWOT matrix is a strategic planning technique used to acquire an overview of a company's current situation. This by identifying the objectives of the business venture and identifying the internal and external factors that are favorable and unfavorable to achieving those objectives. Internal factors are strengths and

weaknesses while external factors are opportunities and threats (Phillip Kotler 2013).

	HELPFUL	HARMFUL
INTERNAL	STRENGTHS	WEAKNESSES
EXTERNAL	OPPORTUNITIES	THREATS

8.3 Porter's Five Forces

Porter's five forces is a model for analysing competition of a business and understanding the structure of its industry. The tools of analysis are five forces - the threat of substitute products or services, the threat of established rivals, the threat of new entrants, bargaining power of customers and bargaining power of suppliers (*How Competitive Forces Shape Strategy* 2019).

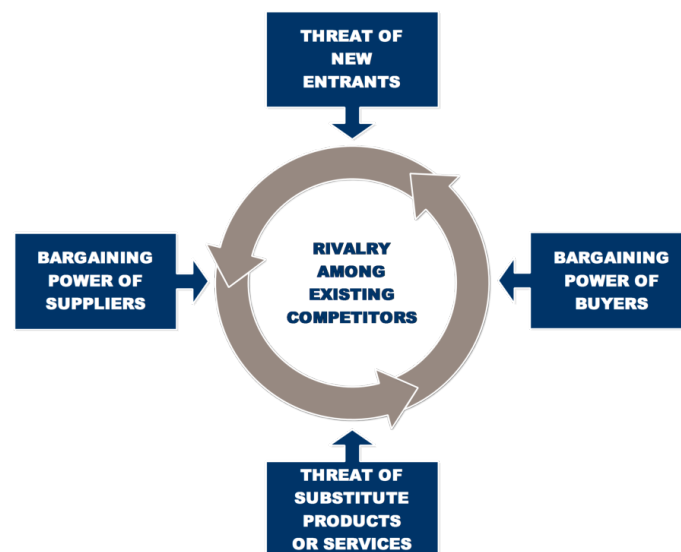


Figure 8.1: Porter's Five Forces

1. Threat of New Entrants. New entrants to an industry intensifies the existing competition. Entry barriers have an effect on how much of a threat new entrants could pose. Porter presented a number of different factors, such as capital requirements, government policy and access to distribution channels.
2. Threat of Substitute Products or Services. Substitutes are always present. However, they can be easy to overlook since they appear to be so different from the product in question. The threat of a substitute is high if it has an attractive price-performance trade-off to the product and the buyer's cost of switching to the substitute is low.
3. Bargaining Power of Buyers. Buyers on the market can have a powerful role. They can for instance force down prices, demand higher quality or better service – thereby lowering industry profitability. This is especially a threat if buyers are price sensitive in this area.
4. Bargaining Power of Suppliers. In the same way as buyers, suppliers can force down industry profitability. Suppliers can become powerful if the supplier group is more concentrated than the group it sells to.
5. Rivalry Among Existing Competitors. Rivalry within the industry comes in many different forms, such as new product innovations, price discounting, powerful advertising and service improvements.

In the paper "Designing Interactive Strategy" authors Normann and Ramirez argue that models similar to Porter's Five Forces are industry based and do not adequately capture strategies for companies in fast-changing competitive environments. Seen from the traditional industry perspective, strategy is primarily the art of positioning a company in the right place in the value chain – the right business, the right products, market segments and the right value-adding activities. Global competition, changing markets and new technologies are opening up qualitatively new ways of creating value. In so volatile a competitive environment, strategy is no longer a matter of positioning a fixed set of activities along a value chain. Increasingly, successful companies do not just add value, they reinvent it. Their focus of strategic analysis is not the company or even the

industry but the value-creating system itself, within which different economic actors—suppliers, business partners, allies, customers—work together to co-produce value (*Designing Interactive Strategy* 2019).

9 Results

9.1 Interviews with Racefox

9.1.1 Christer Norström

According to Director of Board and Co-Founder Christer Norström, predictions of oxygen consumption are valuable to Racefox and their customers in the aspect of "early warnings" while running. Running at different velocities over certain distances impose individual threshold plateaus that when exceeded result in physical degeneration in form of example lactic acid, rotating torso and stiff legs, leading to a decreased efficiency in running economy. With the functionality of predicting oxygen consumption these threshold breaches can be avoided with the real-time digital coach recommending to slow down or adopt in a certain way to the demand of the terrain, always taking in to consideration the ability of the individual runner.

The interview also revealed that Racefox launched their sensor as a necessary step to become an established and trusted actor in the market. In the long run an ambition according to Norström is to become completely software based providing artificial intelligence for movement data in wearables in collaboration with hardware-based companies. This can be applied to all sorts of movement data, such as injury rehabilitation or smart sport components. Today Racefox Ski in collaboration with leading ski equipment company Rottefella provide a ski binding that understands the demands of the terrain and the ability of the skier and adapts accordingly while skiing (*Racefox-Rottefella* 2019).

Furthermore, Racefox market their service in collaboration with sport events Lidingöloppet, Göteborgsvarvet and Vasaloppet. Norström believes this is a great way of advertising the service for engaged customers who will participate in a coming race. The slogan used for Göteborgsvarvet is "What does it take to race Göteborgsvarvet at your dream time?", signaling that with this service they can show what it takes and how it is done. The interview revealed that Racefox increased the price in attempt to attract the right kind of customers, individuals who actually are interested and will benefit from this service. Initially Racefox sold

the sensor and application solution as a product but soon switched to subscription service. This according to Norström is because it is much more in line with the company value proposition; helping individuals become better runners instead of having to continuously sell sensors to become financially sustainable.

Norström also stated during the interview that companies who provide social networks and are owned by sporting clothes-, equipment- and shoes-producers can according to Norström be viewed as a channel for these companies to connect to their users. This adds value to their physical training products and markets them. Examples are Runkeeper that is owned by ASICS, Endomondo owned by Under Armour and Nike Runners club owned by Nike.

9.1.2 Bernhard Hirschauer

Targeted market segmentation's of Racefox today are active and ambitious runners and skiers on the Swedish and Norwegian market. This group can have shown to consist of generally older customers, spanning from 35 years and older. Furthermore Hirschauer stated that the strategic partnerships with large sport events are a great win-win situation for both parts, great platform for coming in contact with the right customers, selling the service in a package with the preparations for a race and gives value for the sportevent organisers with added features for its runners. The interview also revealed that Racefox want to continue expanding with sport event partnerships especially a half-marathon and marathon, these could even be international races as for example Berlin Marathon or New York Marathon.

The interview revealed that Racefox will not release a next generation sensor with added specifications but rather strive towards becoming entirely software-based. The ambition is to enter strategic partnerships with leading hardware providers and providing the running dynamics intelligence. This means that also the mobile phone which today is a necessary tool for collecting data while running will be replaced with something similar to a smartwatch or sportwatch which can in real-time process, store and upload data.

He also points out that with the ability to predict oxygen consumption, precision

in models will increase. Max heart rate is used today which is built on normality assumptions. Oxygen consumption in turn also has a degree of assumptions as it is calculated with proxy values, these different methods measure the same result with can cross-reference and be used to calibrate models after individuals.

9.2 Running technology industry

The conclusion after interviews and market segmentation research is that the value offered to customers in the running technology industry can be categorised as: applications, sensors, services and smart gear. These domains together construct the running technology ecosystem. There are of course nuances within these domains. Industry operators have different products, services and partnerships within this ecosystem which lays the foundation for the industry dynamics.

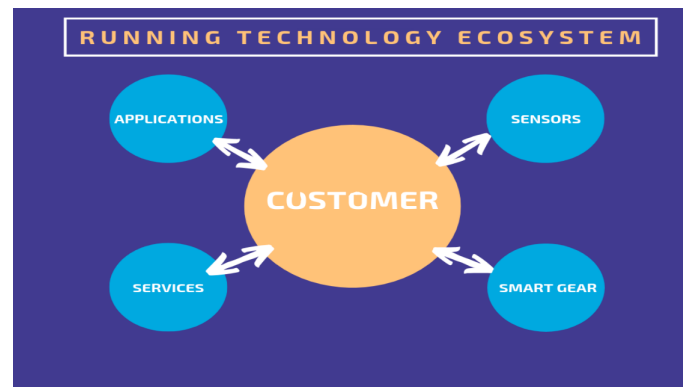


Figure 9.1: *Running technology ecosystem*

A heat map has been constructed based on conducted interviews, market research and analysis of industry actors products and services. The purpose of this heat map is to give the reader a grasp of leading actors products and services provided. This heat map should serve as an accessible overview of leading and relevant actors and should be used with caution as an basis for decision making as it is simplified.

- Applications is defined as accessible user interfaces and powerful functionality corresponding to the companies products and services.

- Sensors is defined as hardware that collect running data.
- Smart gear is devices that can process and analyse data, some smart gear both collect and analyse data.
- Running analysis is defined as analysis and feedback of the collected running data.
- Social networks is defined as a platform for communities and individuals to upload, share and interact with running exercises and measurements.
- Health solutions is defined as sensors and/or smart gear that present health and life-style related metrics which aim to change and improve customers overall health such as sleep, exercise, diet and stress.

Table 9.1: Heatmap over leading industry actors product and services

Company	Applications	Sensors	Smart gear	Running analysis	Social networks	Health solutions
Racefox						
Garmin						
Polar						
Suunto						
Stryd						
Endomondo						
Strava						
Fitbit						
TrainingPeaks						
Excellent						
Good						
Fair						
Poor						
Non-existing						

9.3 SWOT

This a SWOT analysis of Racefox constructed on the basis of market research, interviews and previous studies.

	HELPFUL	HARMFUL
INTERNAL	Strengths <ul style="list-style-type: none"> • Movement data analysis • Skiing analysis leading • Sport event partnerships 	Weaknesses <ul style="list-style-type: none"> • Hardware • Weak brand name • Small scale
EXTERNAL	Opportunities <ul style="list-style-type: none"> • Movement data analysis and intelligence provider • Strategic partnerships • International expansion 	Threats <ul style="list-style-type: none"> • Competition from established actors (Garmin etc) • Customers don't understand the products benefits or lose interest due to lack of continuous insights

Figure 9.2: A SWOT-analysis of Racefox in the running technology market

9.4 Porter's Five Forces

1. Threat of new entrants - The market for running technology is quite established as the concept goes for either creating a platform for social networking among runners and smart gear/hardware manufacturing by market dragons such as Garmin, Suunto and Strava. The movement pattern analysis is a newer technological area with higher threat of new entries.
2. The threat of substitutes are currently high for Racefox since of following reasons:
 - Free but more basic services provided by social network companies offer a attractive price-performance trade off for customers interested only in more standard measurements such as distance, time and exercises planning.
 - Expensive but sophisticated smart gear (often smartwatches) on the market that provide both movement analysis and health and lifestyle-related metrics for customers.
3. Bargaining power of buyers is high within in the market for running technology since the product and services for a majority is not necessary.
4. Bargaining power of suppliers is with the current Racefox business model low as subcontracting is limited down to one standard heart rate strap.

5. Rivalry Among Existing Competitors - For the customers in the ecosystem of running technology there are a wide range of competitive companies within all the domains. Some market giants provide products and services to some extent within all domains which creates certain degree of internal lock-in due to compatibility issues. Competition in domains smart gear and sensors is high and large scale of production is needed for profitable margins. Within the domain services, running analysing and further more actionable insights and interpretation of the measurements is low. Exit barriers from running or skiing to another movement pattern analysing area are low for Racefox.

10 Discussion

10.1 Evaluation using SWOT-analysis

Strategic insights from the SWOT-analysis are that Racefox current edge is their competence within movement pattern analysis within running and skiing and explaining this information in a utilisable way for their customers. Furthermore partnerships with sport events give Racefox valuable marketing and add value to participating customers. A opportunity in building the brand name is to take part in similar partnerships for international races, especially to include the popular events such as Berlin, Boston or New York Marathon. Racefox furthermore has potential in expanding its current knowledge and infrastructure into more movement analysis applications such as sports, injury rehabilitation and making clothing/accessories more intelligent.

Despite these strengths and opportunities Racefox have weaknesses and threats that might cause a unsuccessful market establishment. Threatening is that Racefox is small and the brand is not well know which as a great disadvantage compered to large industry actors that are well known and have a range of compatible products and services. Racefoxs hardware is a weakness with one robust but simple sensor and customers own mobile phone is necessary as smart gear. Competition on manufacturing smart gear and sensors is high and large scale production is needed to produce profitable margins. Furthermore customer behaviour can be a threat. Hard to use or decreasing beneficial/useful insights customers might loose interest and quickly unsubscribing to the Racefox service.

10.2 Evaluation using Porter's Five Forces

Porter's Five Forces show that competition is high within all ecosystem domains except movement pattern analysis services. This makes the threat of new or already established companies entering this area high. Will market dragons such as for example Garmin invest heavily in this area if it turns out to be

lucrative or will they want to partner with Racefox and outsource this service? The outcome is vital for Racefox's competition situation and position within the market structure.

If the current business strategy with Racefox's own sensor and analysis is maintained threat of substitute products and services are high. Start-ups can compete or as mentioned global leading actors as Garmin or Suunto can invest heavily and acquire majority of market share essentially locking Racefox out from the market. Racefox will have hard competing within hardware as margins are low and large volume production is needed. Also appealing for customers are free services offered by many of the leading social networks for runners providing more standard measurements as distance, time and GPS tracking. Market segmentation seeking advanced smart gear with both running analysis combined with health and lifestyle related metrics will go for premium smart gear products that leading companies offer. Racefox needs to provide more value per cost than substitutes for the market segmentation who specifically want to engage actively in his or her training and optimising their training. Bargaining power of buyers is high as the service is not necessary and many free but more basic alternatives are available.

This changes if Racefox change their overall strategic ambition more in line with the "Designing Interactive Strategy" by authors Normann and Ramirez which conducted interviews indicate. With a entirely software based company Racefox will become business to business instead of business to customer which changes the Porters Five Forces analysis. With more sophisticated and practically utilisable insights that Racefox can provide to a leading hardware company's data value is added to its customer, giving Racefox a strong bargaining power as buyers will have their services integrated into company hardware. As subcontracting will be minimal as software based bargaining power of suppliers will be low. Having strategic partnerships with global hardware manufactures will eliminate Racefox's weakness with hardware and significantly decrease the threat of being locked out of the market by well known international brands investing heavily in movement pattern analysis.

10.3 Racefox's Product and Service Strategy

Based on the theoretical tools implemented on Racefox current product and service strategy should be to seek partnerships with leading sensor and smart gear manufactures enabling Racefox to becoming entirely software based. Racefox will then become a business to business actor providing sophisticated and actionable insights regarding movement pattern data, currently including running and skiing but in the future more applicable fields should be included as smart clothing, smart accessories and injury rehabilitation. Furthermore partnerships with sport events give Racefox valuable marketing and add value to participating customers. A opportunity in building the brand name is to take part in more of these races, especially international half-and full marathons.

11 Conclusion

To answer the research questions asked in the beginning of this paper: The oxygen consumption can be predicted using Racefox's KPIs, with quite a high accuracy on one subject. This accuracy can be improved with more observations, which would probably yield higher accuracy on multiple subjects and thus improve the service offered by Racefox.

Implementation of this model in Racefox's service will improve the service by offering further individualisation of the feedback received after each track. This can further be used to implement "early warning systems", to prevent running economy deficiency during exercise. However, this project found that Racefox should focus on company core competence running analytics and becoming entirely software based through strategic partnerships with hardware manufacturers. Prediction of oxygen consumption would then be a part of the running analytics package offered by Racefox through sensors and smart gear of partners.

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