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Version: Accepted Manuscript

Link(s) to article on publisher's website:

<https://webscience-journal.net/webscience/article/view/44/30>

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Pro-Environmental Campaigns via Social Media: Analysing Awareness and Behaviour Patterns

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ABSTRACT

Changing people's behaviour with regards to energy consumption is often regarded as key to mitigating climate change. To this end, endless campaigns have been run by governments and environmental organisations to engage and raise awareness of the public, and to promote behaviour change. Nowadays, many such campaigns expand to social media, in the hope of increasing their reach and impact. However, in spite of persistent efforts, public engagement with these campaigns tends to be rather underwhelming. This demonstrates the need for adopting new strategies in designing and executing these campaigns. To the best of our knowledge, these campaigns often overlook existing theories and studies on user engagement and behaviour change. To close this gap, this paper uses Robinson's Five Doors Theory of behaviour change [26] to analyse online user behaviour towards climate change. With this approach, users' behavioural stages can be automatically identified from their contributions on social media. We apply this approach to analyse the behaviour of participants in three global campaigns on Twitter; United Nations COP21, Earth Hour 2015, and Earth Hour 2016. Our results provide guidelines on how to improve communication during these online campaigns to increase public engagement and participation.

Categories and Subject Descriptors

Human-centered computing [Social networking sites]:

Keywords

Behaviour Analysis, Social Media, Climate Change

1. INTRODUCTION

Climate change is now widely accepted to be a major threat to world's ecology, health, safety, and economy [31]. Pressure has been increasing on governments and policy-makers to take firm and decisive action to mitigate the severe and rapidly growing impact of climate change. This was the basis for holding the United Nations 2015 Paris Climate Conference (COP21), which produced strict and ambitious national and international carbon emission reduction targets.

However, it is often forgotten that a significant impact on our climate in fact comes directly from citizens, rather than from governments. Households' greenhouse gas emissions form 19% of the global annual amount, third behind emissions from the energy sector (27%) and industry (26%).¹ In light of this, one of the COP21 agreements was to focus on changing people's energy consumption behaviour. To this end, several global campaigns and initiatives have been launched with the aim of involving individuals more closely in the solution to this global problem.² One of the core mediums used by such campaigns to communicate with the public worldwide are social platforms, such as Twitter and Facebook, as a way to widen their reach and impact.

Nevertheless, in spite of these evidences, policies, and campaigns, public engagement appears to be quite limited [31]. This could be attributed to several factors, such as that most people do not appreciate the impact of their individual behaviour on global climate, or understand their power in influencing climate change, or how to improve their energy consumption habits [29]. Furthermore, it is often difficult to know what type of audience these campaigns are reaching and engaging. Particularly it is difficult to determine whether citizens, or other type of social media accounts, such as those representing organisations, are the ones more involved in the campaigns.

Parallel to the generation of these initiatives and campaigns, multiple theories have emerged from psychology and social sciences that aim to model and investigate the motivations that drive people to getting involved and to changing their own behaviour, and how these behavioural changes happen with regards to energy consumption. However, it remains unclear how such theories can be applied in real scenarios and campaigns, to render such organisational communication strategies more effective on the public.

For example, the amount of traffic generated on social media around major campaigns tends to be vast (more than 2.5 billion Twitter impressions and over 18.7 million Facebook impressions were reported for the Earth Hour 2016

¹<http://ec.europa.eu/eurostat/news/themes-in-the-spotlight/cop21>

²<http://www.theguardian.com/global-development-professionals-network/2013/nov/15/top-10-climate-change-campaigns>

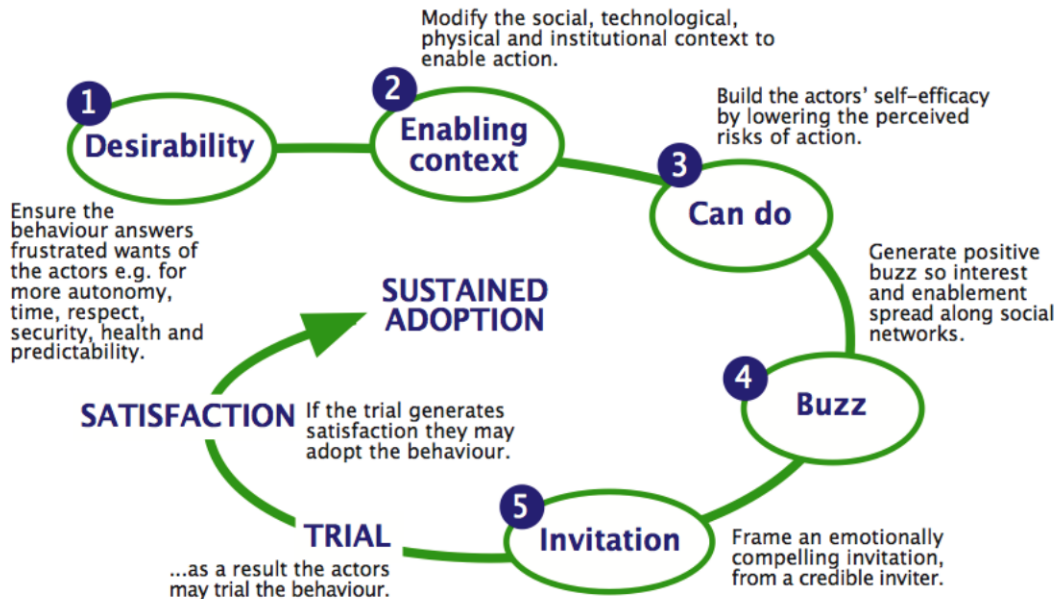


Figure 1: 5 Doors theory of behaviour change

campaign³). In such highly active and dynamic environments, it is difficult to assess and understand how these campaigns were received, or the type of social media accounts that received them. Manual analysis is impractical, and thus automated techniques need to be developed and deployed. However, it is unclear how this social data should be analysed, and how to gain useful insights that can ultimately be used to improve communication, and in turn to influence behavioural change.

Simple statistical analysis of outreach is insufficient for gaining rich insight; especially without understanding who is being reached through the campaign, who is disseminating messages related to the campaign, and what the semantics of these messages are. Such deeper understandings can help to better correlate social communication with environmental behaviour, i.e., not only whether people responded to a tweet, but also *how* they responded to these tweets, and *who* they are (whether it is an individual or an organisation). To bridge this gap, our work investigates two main research questions:

1. *How can we translate theories of behaviour change into computational methods to enable the automatic identification of behaviour?* We propose an approach based on Natural Language Processing (NLP) and Machine Learning (ML) that automatically identifies the different behavioural stages which users are at, by filtering and analysing large amounts of user-generated content from social media. We follow in our approach the behavioural stages identified by Robinson [26] in his 5 Doors Theory of behaviour change.
2. *How can the combination of theoretical perspectives and the automatic identification of behaviour help us to develop effective social media communication strategies*

for enabling behaviour change? We combine the learnings from different theories towards awareness, engagement and behaviour with the learnings acquired after analysing online behaviour from three large-scale social media movements, and translate these into a set of social media campaign recommendations.

By investigating these research questions, we provide the following contributions:

1. Summarise and analyse a range of social science theories around awareness, engagement and behaviour change;
2. Develop a user categorisation approach capable of distinguishing individuals vs. organisations on Twitter;
3. Develop a behaviour analysis approach capable of identifying users' behavioural stages, based on their contributions on Twitter;
4. Generate a set of recommendations to enhance social media campaign communications, based on combining theoretical perspectives with analysis of three large-scale social media environmental movements.

The following sections are structured as follows: Section 2 describes the scenarios, or social media movements, analysed in the context of this research. Section 3 describes a compendium of different theories of awareness, engagement and behaviour change. Section 4 shows our proposed approach to automatically identify different stages of behaviour towards climate change based on the users' social media contributions. Section 5 describes our experiments to categorise users into behavioural stages using the analysis tools. Section 6 discusses our recommendations for social media environmental campaigns based on our study of the literature and the result of our analyses, while Section 7 concludes.

³<https://www.earthhour.org/sites/default/files/Earth\%20Hour\%202016\%20Report.pdf>

2. USE CASE SCENARIOS

We analyse behaviour in the context of three of the largest and more recent movements for climate change reflected in social media: Earth Hour 2016 (EH2016) and 2015 (EH2015) and the 2015 United Nations Climate Change Conference (COP21).

Earth Hour (EH)⁴ is a large-scale campaign launched by the World Wide Fund For Nature (WWF) every year to raise awareness about environmental issues. The event aims to encourage individuals, communities, households and businesses to turn off their lights for one hour, from 8:30 to 9:30 p.m. on a specified evening towards the end of March, as a symbol for their commitment to the planet. It started as a lights-off event in Sydney, Australia in 2007. Since then it has grown to engage more than 178 countries worldwide.⁵ Today, Earth Hour engages a massive mainstream community on a broad range of environmental issues. The one-hour event continues to remain the key driver of the now larger movement. WWF's Earth Hour is a unique opportunity to understand user engagement and behaviour towards climate change, and the possibilities to facilitate more sustainable behaviours.

COP21 is the 2015 United Nations Climate Change Conference. This conference was held in Paris, France, from 30 November to 12 December 2015. The conference negotiated the Paris Agreement, a global agreement on the reduction of climate change, the text of which represented a consensus of the representatives of the 196 parties attending it. COP21 is part of a series of periodic meetings, that began at the Rio Earth Summit in 1992, where the highest world authorities debate thresholds between socio-economic development and carbon emission reduction, and try to produce consensual plans to control the impact of climate change. Multiple organisations, including WWF, launched social media campaigns around COP21, generating a large world-wide social media reaction. This movement is a reflection of society's pressure on governments to commit to the agreements and to make better environmental choices.

3. AWARENESS ENGAGEMENT AND BEHAVIOUR CHANGE

As mentioned in the introduction, people typically do not understand the correlation between their individual behaviour and its global impact, thus underestimating their power to influence climate change. In particular, the lack of self-efficacy is one of the reasons that prevent people to take part in the climate change battle [29]. The impact of individual behaviour on the global scenario is not obvious, and people usually underestimate their power to change reality.

Understanding the mechanisms that govern behaviour with regard to energy use, and fostering changes towards conservation, has been a topic of investigation in the domain of social and environmental psychology [1], in computing technology [17], and in interactive design [18]. Understanding behaviour and its change in general is also widely discussed in marketing and advertising, particularly by using social media [6][30][26][4][14].

In this section, we first take a look at theoretical studies to get insights into which communication strategies have

⁴<https://www.earthhour.org/>

⁵<https://www.earthhour.org/sites/default/files/Earth\%20Hour\%202016\%20Report.pdf>

been proposed to influence people's behaviour in favour of a product or idea. We dissect the more general studies, and then focus on studies about behavioural change. By analysing these studies we aim to look at the following aspects: how do we get people informed? How do we get people to talk and discuss? How do we make people feel connected to the cause? How do we get people to act in new ways (behavioural change)? And how does this relate to behaviour with regard to climate change and energy use? As a result of the analysis of these theories, we propose a set of strategies that can be used to promote awareness, engagement and behaviour change using social media as a medium.

3.1 Awareness and Engagement

The first issue a campaign needs to consider is awareness, i.e., how to make users aware of the topic, in our case climate change, and aware of their own behaviour towards the topic. One of the key recommendations proposed by Ariely [4] is that the user not only needs to be aware of the subject, but they also need to be aware of the various options to act. To have impact, the first thing a campaign needs is *to have a clear story to tell, with a very concrete action connected to it*. This is particularly complex in the case of campaigns towards climate change, since it is a very broad subject that represents many different smaller stories, connected to multiple behavioural actions. Campaigners should therefore be able to break down those stories and actions for the public.

In addition to the previous recommendations, Berger [6] highlights the need for "word of mouth", i.e. the need for social transmission, or social influence, to spread the message and increase awareness. Berger and his colleagues analysed several viral campaigns and concluded that to make a campaign "engaging" it should follow the six principles of contagiousness, or STEPPS: *Social currency* (people share things that make them look good); *Triggers* (it is part of the users' everyday life, and on top of their minds); *Emotional resonance* (when users care about something, they share it with others); *Public* (the idea or product is built to show and built to grow); *Practical value* (people like to share practical or helpful information); and *Storytelling* (people tend to share stories, not information). Climate change campaigners should therefore focus on creating *innovative useful messages with an emotional undertone and a memorable story line*.

Vaynerchuk [30] emphasises the issue of differentiating each social medium when communicating a story, since different social media platforms are generally used for different needs and use different algorithms to promote content in the users' news feeds. It is therefore important for campaigners to *get familiar with the different social media platforms where the campaign will be communicated*.

Works like Campbell [8], Kazakova [20], Cheong [10] and Proskurnia [25] have focused on analysing the characteristics of the climate change social media campaigns, including previous editions of EH, and the mechanisms used to engage with the public during these campaigns. The work of Fernandez [15] complements these by studying the effect of some of those mechanisms and their impact on public engagement. This study concludes that, in the context of these campaigns, *more engaging posts tend to be slightly longer (in the case of Twitter they use nearly all 140 characters available), are easier to read, have positive sentiment*

and have media items (original/funny photos linked to the message) associated to them. Also, symbolism needs to be focused around climate change related topics. Superheroes, celebrities, and other types of symbols that are sometimes associated to these social media campaigns, create buzz but do not generate awareness or engagement towards climate change. Proskurnia [25] adds to these conclusions the fact that first-degree neighbours are essential to drive user engagement, i.e., popular users with a higher number of engaging followers are key to propagating the message during social media campaigns.

3.2 Behavioural Change

Environmental campaigns not only aim to raise awareness and create engagement, but ideally also to trigger behavioural changes, for instance by encouraging individuals to reduce their consumption of energy. Different scientific domains such as psychology, anthropology, sociology, and philosophy have put effort into understanding the forces that drive people’s behaviour around protecting the natural environment [7], [11]. This “not emotionally neutral subject” [28] has been conceptualised as Behaviour Change Theory, a field of study that transcends environmental purposes, being also applied to health, education and dissemination of new products or concepts.

Behaviour Change Theory is mainly dominated by two complementary approaches: models of behaviour and theories of change. Models of behaviour can be applied to understand specific behaviour and identify factors of influence, mainly at the individual level [13]. Theories of change, on the other hand, explain the behavioural change process through social science lenses, being particularly helpful for developing interventions leading to a desired behaviour change. Theories are more generic, usually not taking into account contexts, perceptions and needs of a particular group of people [26].

By integrating a number of formal theories from psychology and social sciences in terms of “what it takes for new practices or products to be adopted by groups of people”, Robinson developed the 5 Doors theory [26]. This generic theory aggregates elements from Diffusion of Innovations [27] and the Self-Determination theory of motivation⁶, among others. Instead of promoting changes to people’s beliefs or attitudes, the 5 Doors theory focuses more on “enabling relationships between people and modifying technological and social contexts”.

The theory consists of 5 conditions that must be present in a cycle of behaviour change (see Figure 1). It is important to highlight that when mapping this theory to analyse user behaviour, our interpretation is that each of these conditions maps to a different behavioural stage, our assumption being that users shape their social media messages differently according to the stage which they are at:

- *Desirability*: For someone to adopt a new behaviour into their lives, they have to want it. People in this stage are motivated (desire) to reduce their frustrations, which can be about day-to-day inconveniences (e.g. high expense on their electricity bill), or about deeper personal frustrations (e.g. living in a less polluted environment to recover lost health);

- *Enabling context*: People in this stage are changing their environment to enable a new behaviour. That includes infrastructure, services, social norms, governance, knowledge – literally anything that could exert a positive or negative influence on a specific behaviour;
- *Can do*: People in this stage are already acting. This stage focuses on increasing the person’s self-efficacy and lowering the perceived risks of change by building a set of tactics;
- *Positive buzz*: People in this stage communicate their experiences and success stories, which helps create buzz and increase other people’s desires;
- *Invitation*: People in this stage invite and engage other people to their cause. Who issues the invitation is vital to engage others. A good inviter wins people’s attention and commitment by authentically modelling the change in their own lives.

The 5 Doors theory correlates closely with empirically generated theories of behaviour, such as the one developed by Green Energy Options (GEO)⁷ when conducting energy trials.⁸ This model consists of five stages that refer to the level of awareness and involvement with a cause and the sort of tactics a sender should employ to nudge the user in the direction of change: (i) *Enrol*: establish means to generate / spread interest; (ii) *Educate*: help people understand/ gain confidence in their ability; (iii) *Engage*: facilitate to take action; (iv) *Encourage*: provide feedback and encouragement; and (v) *Expand*: provide opportunities to share and expand.

Since intervention strategies, or tactics to nudge the user in the direction of change, are generally different according to the stage in which the user is, it is important for campaigners to: (i) identify the different behavioural stages of their audiences in order to generate more targeted strategies, and (ii) to make sure that a campaign is covering all possible stages so that all users find support to progress. A key contribution of this research is therefore directed towards providing computational methods able to automatically categorise users into different stages of behaviour based on their social media contributions (see Section 4).

3.3 Intervention Strategies

Intervention strategies are used when aiming to change behaviours. Multiple works in the literature have emerged in the last few years studying the effects of different intervention strategies, particularly with the goal of reducing energy use [1], [18]. While Abrahamse [1] analyses interventions from the social and environmental psychology perspective, Froehlich [18] focuses on how to design for eco-feedback within the human-computer interaction context. Based on [1] and [18], in this section we summarise a set of popular interventions that can be applied to social media campaigns.

- *Information*: Providing information is a main intervention. However, it is also very important to consider the way the information is presented (whether it is simple to understand, easily remembered, attractive, and provided at the right place and time). Some

⁷<http://store.greenenergyoptions.co.uk/>

⁸http://www.decarbonet.eu/wp-content/uploads/sites/23/2014/10/D5-1_final.pdf

⁶https://en.wikipedia.org/wiki/Self-determination_theory

Table 1: Social Media environmental campaigns: recommendations to increase awareness

Behaviour Stage	Intervention Strategies
Desirability	Providing <i>Information</i> in an attractive way (see Section 3.1), and proposing <i>dilemmas</i> to trigger discussion about the extend of the problem and its impact are some of the interventions that can help users in this stage
Enabling Context	<i>Information</i> , <i>rewards</i> and <i>incentives</i> are important intervention strategies at this stage. Providing appropriate links to dedicated portals so that the user can learn about her options, as well as providing rewards and incentives can help motivating the user for change. Also having access to the personal experiences reported by other users via social platforms
Can Do	Helping the user to set realistic <i>goals</i> and promoting <i>public commitments</i> via social media (e.g., link to petitions to be signed) are some of the strategies to help users to drive their change further. In addition, providing frequent and focused <i>feedback</i> and challenge negative thoughts are also strategies to build self-efficacy
Buzz	Providing <i>feedback</i> , as well as <i>social feedback</i> (i.e., encourage the user to share their success stories, comment over them and help them to discuss their achievements with their peers) are some of the intervention strategies recommended at this stage
Invitation	<i>Promoting collaboration</i> , i.e., encourage the users to invite and collaborate with others to reach a bigger achievement

strategies on how to make messages engaging in social media campaigns are summarised in Section 3.1.

- *Discussions*: Sometimes it is useful to encourage discussions and debates, and social media platforms provide the technical capabilities for such matters. Discussions can be triggered by raising questions or dilemmas, i.e. difficult choice questions confronting pro-environmental behaviour and personal values (e.g., cold showers or no internet for a week?).
- *Public Commitment*: A way of committing to a cause is to publicly pledge or promise to do something to change behaviour. Both the type of commitment, and the person or group to whom the commitment is made, are factors that impact behaviour. Campaigners should propose that users engage with pledges or other concrete actions, and make their commitment public.
- *Feedback*: Feedback about the users' actions, alone or in combination with other strategies, particularly advice, seems to be an effective intervention. Providing feedback, however, requires a higher dedication from campaigners, since it implies bi-directional dialogues where campaigners do not only act as broadcasters but also actively engage in conversations.
- *Social Feedback*: Social Feedback covers all types of social context for comparison and discussion among peers. It includes comparison of energy use across users and dialogue among individuals about their habits and behaviours towards the environment. To generate social feedback, campaigners should stimulate discussions and encourage users to share their experiences with others.
- *Goal-setting*: Setting goals is a motivational technique. Goals can be established by users or by third parties, but should be kept feasible. Campaigners should design and promote a set of feasible goals and encourage users adopt them.
- *Collaboration*: Collaboration aims at aggregating efforts to reach a bigger achievement. It brings a set of individuals together to act towards a common goal.

Establishing collaboration initiatives by local teams as part of a campaign, and encouraging users to get involved, are some actions to consider as part of this intervention.

- *Competition*: The effectiveness of competition has proved sometimes controversial in the studies performed by Froehlich [18] and Abrahamse [1], with some positive but not so evident results in terms of behavioural change. As with collaboration, games and competitions can be prepared as part of environmental campaigns.
- *Rewards*: Rewards provide extrinsic motivations, usually with the intent to promote a short-term behaviour change. Providing monetary rewards or other prizes are examples of actions that can be considered within the context of a campaign.
- *Incentives*: Incentives are an alternative to rewards, mostly aimed at starting and continuing behaviour. Acknowledgements of positive behaviour, and ensuring the users are having fun while engaging with the environment, are examples of possible incentives.
- *Personalisation*: Personalisation strategies are less common in the literature. Within the context of large social media campaigns, generic messages are provided rather than targeting specific individuals. In this work, we move a step forward in this direction by identifying different subgroups of users according to their behaviour expressed online (see Section 4).

These different intervention strategies can be used alone or combined to promote or influence a behaviour change. According to [26], people in different stages of behaviour change can be influenced by different incentives (or interventions). A summary of the intervention strategies that can be considered to encourage a behavioural change at each stage is presented in Table 3.2. This mapping builds on Robinson's theory [26] and on our previous analysis on the role of social media in the perceptions and behaviours towards climate change [23].

3.4 Barriers to Change

An additional element to consider when aiming to change users’ behaviours is the *barriers to change*. Ariely and colleagues [5] identified four main barriers:

- *Friction*. Changing behaviour, however small, always meets resistance. When communicating via social media, the sender needs to reduce friction and resistance as much as possible by giving the user tips and advice.
- *The pain of acting now overshadows delayed benefits*. Climate change is often seen as a vague, abstract problem with far away consequences. Communication strategies need to highlight how a person’s actions really matter.
- *People don’t think about the benefits at the right time*. It is therefore important to work on communicating the benefits clearly and recurrently, rather than hoping people will later remember them.
- *People do not agree it is a good idea*. If people do not believe that climate change is real, then it is important to find other benefits to tie to the desired behaviour (e.g. prizes or monetary rewards). However, behaviour promoted by rewards does not tend to be long-lasting.

4. APPROACH

In Section 3.2, we highlighted our assumption that different users in different behavioural stages communicate differently. Our first task has therefore been to validate this assumption by conducting an online survey (Section 4.1).

Having acquired an understanding of how different behavioural stages are communicated, we developed an approach for automatically identifying the behavioural stage of users, based on three main steps: (i) a manual inspection of the user-generated content (in our case Twitter data) to identify how different behavioural stages are reflected in terms of linguistic patterns (Section 4.2); (ii) a feature engineering process, in which the previously identified linguistic patterns are transformed into numerical, categorical and semantic features, which can be automatically extracted and processed (Section 4.3); and (iii) the construction of supervised classification models which aim to categorise users into different behavioural stages based on the features extracted from their generated content (Section 4.4).

4.1 Social Media Reflection of Behaviour

To test our assumption that users at different behavioural stages communicate differently, we conducted an online survey between September and October 2014 targeting internet users in communities and workplaces. The survey received answers from 212 participants. A description of the elaborated questionnaire, the demographic characteristics of the users who completed it, and an analysis of the obtained answers can be found in [23]. For the purpose of this research, we focus on two main questions from it in which we ask users: (i) how they identify themselves within the five stages of behaviour; and (ii) to provide examples of messages they will post on Twitter. By performing this exercise, we gathered 161 examples of posts associated to a particular behavioural stage. Examples of the messages reported by the users are displayed in Table 2.

In addition to this set of examples, we annotated 100 tweets (a sample of 20 tweets per stage) randomly selected

Table 2: Examples of tweets reflecting the 5 different behavioural stages

Behavioural Stage	Examples of posts
Desirability	- Our buildings needs 40% of all energy consumed in Switzerland!
Enabling context	- I am considering walking or using public transport at least once a week.
Can do	- If you are not using it, turn it off!
Buzz	- I’m so proud when I remember to save energy and I know however small it’s helping
Invitation	- Take 15 minutes out to think about what you do now and what you could do in the future. Read up on the subject and decide what our legacy will be.

from our collected datasets (see Section 5.1). These tweets were annotated by two different researchers. Discussions were raised about those tweets where disagreements were found. If the disagreement could not be resolved, the tweet was marked as ambiguous and discarded. Examples of tweets annotated under each category are displayed in Table 3.

4.2 Manual Inspection of Linguistic Patterns

To identify the key distinctive features of tweets belonging to each behavioural stage, a manual inspection of the previously annotated tweets was performed by two Natural Language Processing (NLP) experts. During this process, a number of linguistic patterns were identified as potentially useful to help characterise the different behavioural stages. The list of identified patterns is given below:

- *Desirability*: Tweets categorised in this behavioural stage tend to express negative sentiment and emotions such as personal frustration, anger and sadness. They usually include URLs to express facts, and questions asking for help on how to solve their problem/frustration.
- *Enabling Context*: Tweets categorised under this behavioural stage tend to be expressed in a neutral sentiment and emotion. They generally provide facts about how to solve a certain problem, in particular numerical facts about amounts of waste, energy reduction, URLs pointing to information, and conditional sentences to indicate that, by performing certain actions, benefits can potentially be obtained.
- *Can do*: Tweets categorised under this behavioural stage tend to be expressed in a neutral sentiment and generally contain suggestions and orders directed to self and others (I/we/you should) (I/we/you must).
- *Buzz*: Tweets categorised under this behavioural stage tend to have positive sentiment and emotions of happiness and joy, since they generally talk about the user’s success stories and about the actions they are already performing in their engagement towards climate change and sustainability.
- *Invitation*: Tweets categorised under this behavioural stage tend to have positive sentiment and emotions of happiness or cuteness, since they are focused about engaging others in a positive and funny way. The text

Table 3: Examples of tweets reflecting the 5 different behavioural stages

Behavioural Stage	Examples of posts
Desirability	- It was such a horrible storm today! Doesn't feel like the normal rain that we are used too isn't it?! Climate change? - Wondering what the grand bargain between the US and China on climate change is going to look like. Without one, we're all in deep trouble.
Enabling context	- Changing a light bulb. Fluorescent Lights last longer, use less energy, and save you money. - Cold air hand dryers utilise high air speed to dry hands quickly, helping to provide ongoing energy savings: http://t.co/8Ssq1aa6xs
Can do	- UN Campaign on Climate Change - sign the petition to Seal the Deal at Copenhagen http://www.sealthedeal2009.org#cop15 - Track your energy savings with this student-developed website #macewanu #yeggreen http://t.co/jckR9XAFKu http://t.co/2V2wEFkg1
Buzz	- Filling my tires and saving one tank of gas per year! Climate Crisis Solution #06 - We thought we'd achieve 10% energy savings thru efficiency. We were SO WRONG. It's 40% so far!
Invitation	- We hope you're all participating in Earth Hour tonight! It starts at 8:30!!! http://t.co/2VI8xxo2IA - I'm switching off for Earth Hour at 8.30pm on 28 March, will you join me? #EarthHourUK http://t.co/eitii1ojqW

generally contains vocative forms (friends, guys) calling others to join the cause.

4.3 Feature Engineering

In order to automatically extract the linguistic features represented in the patterns described above, NLP tools (provided by GATE⁹) were used. These included basic linguistic pre-processing (such as part-of-speech tagging and verb chunking) [12] and more complex tasks such as opinion mining and emotion detection [22]. The tools for annotating tweets are available publicly as a web service on the GATE Cloud.¹⁰ The features extracted were:

- Polarity: positive, negative, neutral
- Emotions
 - Positive (joy/surprise/good/happy/cheeky/cute)
 - Negative (anger/disgust/fear/sadness/bad/swearing)
- Directives
 - Obligative (you must do) - e.g., you must turn off the light
 - Imperative (do) - e.g., turn off the light!
 - Prohibitive or negative imperative (don't do) - e.g., do not turn off the light
 - Jussive or imperative in the 1st or 3rd person - e.g., go me!
 - Deliberative (shall/should we) - e.g., shall we turn off the light?
 - Indirect deliberative (I wonder if) - e.g., I wonder if we should turn off the light
 - Conditionals (if/then) - e.g., ,if you don't turn off the light your bill will increase
 - Questions (direct/indirect)
- URLs (yes/no) indicates if the message points to external information or not

Table 4: Linguistic Patterns per behavioural stage

Behavioural Stage	Linguistic Patterns
Desirability	- Negative sentiment (expressing personal frustration- anger/sadness) - URLs (generally associated with facts) - Questions (how can I? / what should I?)
Enabling context	- Neutral sentiment - Conditional sentences (if you do [...] then [...]) - Numeric facts [consumption/pollution] + URL
Can do	- Neutral sentiment - Orders and suggestions (I/we/you should/must...)
Buzz	- Positive sentiment (happiness / joy) - I/we + present tense) I am doing / we are doing
Invitation	- Positive sentiment (happy / cute) - [vocative] Friends, guys - Join me / tell us / with me

⁹<https://gate.ac.uk/>

¹⁰<https://cloud.gate.ac.uk/shopfront/displayItem/environmental-annotator>

Table 5: Results of the different classification models

Model	Accuracy	Precision	Recall	F-measure
Naive Bayes	61.2%	0.669	0.6	0.67
SVM	62.39%	0.656	0.624	0.612
J48	71.2%	0.716	0.715	0.714

We can clearly see how some of these linguistic modalities correlate with the behaviour model. For example, deliberatives are strongly associated with stage 1 (Desirability), while conditionals are often linked with stage 2 (Enabling context) and jussives with stage 4 (Buzz or self-reporting). However, the boundaries between these stages are often quite fuzzy, and people’s online behaviour will not always correlate exactly with a single stage. We should also note that not every occurrence of one of the linguistic patterns will reflect the correct stage: not every conditional sentence will necessarily reflect the “enabling context” stage, for example. We use these linguistic patterns only as a broad guideline to help with the categorisation. Furthermore, NLP tools are never 100% accurate, and this holds particularly for some of the harder tasks such as opinion mining and emotion detection. Performance varies greatly depending on the task: direct questions can be recognised at near 100% accuracy, but correct assignment of opinion polarity may only be around 70% accurate.

4.4 Behaviour Classification Model

Using the feature extractors, we process the 261 annotated posts, i.e. posts with associated behavioural stages (see Section 4.1), and use them to generate different classifiers. In particular, Naive Bayes, Support Vector Machines (SVM), and decision trees have been tested using 10-fold cross validation. The best performing classifier was the J48 decision tree, obtaining 71.2% accuracy, with the lowest accuracy obtained for the invitation stage (68.7%) and the highest accuracy obtained for the desirability stage (72.6%). Note that short tweets containing just URLs, abbreviations or slang, are difficult to categorised. Decision trees discriminate the most distinctive attributes first and separate the population (in this case the set of posts) based on the identified distinctive features. The generated decision tree provides a multi-class classification by following this approach. Detailed performance of the evaluated models in terms of precision, recall and F-measure is reported in Table 5.

As we can see in Figure 2, the most discriminative feature is sentiment. If the sentiment of the post is negative, the classifier automatically categorises it as stage 1 (desirability). If the sentiment is neutral the classifier checks if the post contains a URL. Posts with neutral sentiment are classified as: stage 1 (desirability) if they do not contain a URL or stage 2 (enabling context) if a URL is present. Note that URLs are an indication of additional information, generally facts associated with the message. If the sentiment is positive, the classifier looks at the type of directive used. If the directive is conditional, deliberative or indirect deliberative, the post is classified as stage 2 (enabling context). If it is obligatory or imperative the post is classified as stage 3 (can do). If there are no directives, or other kinds of directives, in the text, the classifier looks at emotions in order to discrim-

inate. If the emotion is joy, the post is categorised as stage 5 (invitation); if the emotion is happy, good or surprise, the post is categorised as stage 4 (Buzz).

Our model provides an easily understandable set of rules to categorise posts into behavioural stages. To identify the behavioural stage of each user over time, we consider their contributions in a month period, and assign to the user the most popular behaviour stage among their posts. If there is no majority class, or if the user did not post anything related to climate in that period, we consider them as “unclassified”.

4.5 User Categorisation Model

When analysing user behaviour via social media it is important to consider that multiple social media accounts do not represent individuals but organisations, such as Companies, News Agencies, Non-Governmental Organisations (NGOs), etc. Particularly, during the EH and COP21 movements, NGOs such as EH, WWF, GreenPeace, etc. displayed a significant online presence. A key aspect of our work is therefore to be able to differentiate and select those accounts that belong to individuals, so that we can further analyse their behaviour.

While this problem is shared across social media user studies, to the best of our knowledge categorising social media accounts has not been extensively investigated. One of the most well-known initiatives up to date is RepLab 2014¹¹, which has attempted to address this problem in the context of online reputation. This initiative [2] proposed an author categorisation task to classify Twitter profiles with more than 1,000 followers into ten categories: Company, Professional, Celebrity, Employee, Stockholder, Investor, Journalist, Sportsman, Public Institution, and Non-Governmental Organisation (NGO). These categories were selected considering the literature of online reputation. Our goal however is slightly different, since we do not only aim to categorise users with a high number of followers (i.e., users with an established reputation) but to distinguish individuals vs. organisations, independently of their popularity and reputation. We therefore propose an approach to automatically categorise Twitter user accounts into individuals vs. organisations based on three main steps:

- In order to distinguish between different account types, we have collected examples of accounts that belong to individuals and organisations, particularly Companies, News Agencies and NGOs. We have selected these types of organisations due to their strong presence in social media environmental campaigns. User profile information from these accounts has been extracted, downloaded and pre-processed for training purposes.
- Feature engineering has been performed to describe user profile data by processing textual, numeric and media attributes of the collected Twitter profiles.
- Multiple classifiers have been trained and tested based on the selected features and training data, obtaining up to 0.82 F-measure with the best performing model.

These three steps are detailed in the following subsections.

¹¹<http://nlp.uned.es/replab2014/>

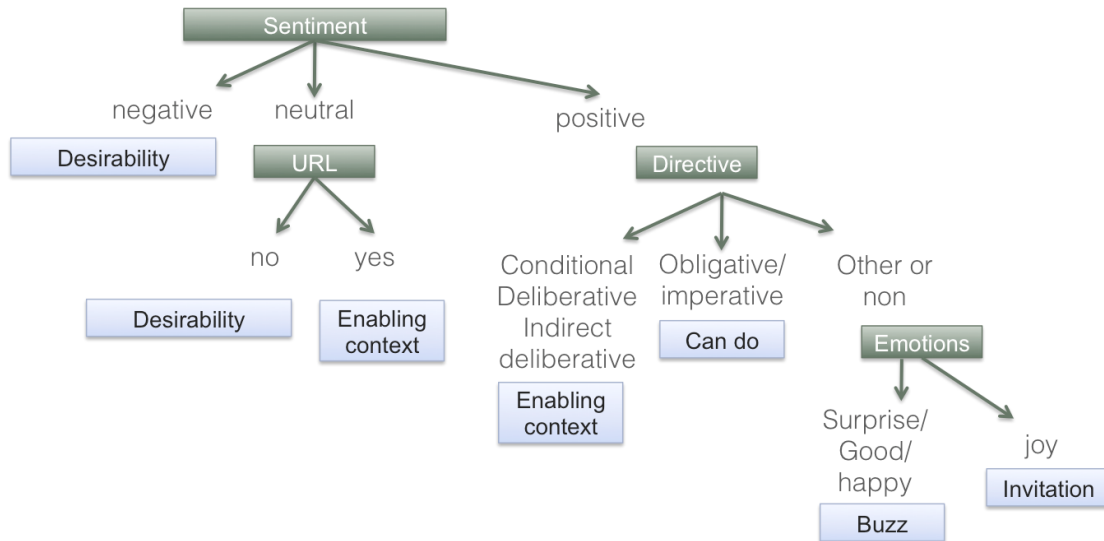


Figure 2: Behaviour classification model

4.5.1 Collecting Twitter Accounts

To obtain examples of social media accounts for the different categories we have made use of Twitter Lists. A Twitter list is a curated group of Twitter accounts. Any Twitter user can create lists and can also subscribe to the lists of other users. At the moment, Twitter does not provide any specific functionality to search for Twitter Lists, but these lists are indexed by Google, which enables a thematic search of the available Twitter lists. For example, to search for Twitter Lists about companies, we performed the following query via the Google search engine: *site:twitter.com inurl:lists company*. Lists were then sorted via their popularity (i.e., the number of subscribers), and the user accounts of the top 15 lists for each category were crawled using the Twitter API. We collected total of 3,283 accounts using this method, along with their corresponding attributes (name, description, number of followers, etc.), leading to 1726 Twitter accounts representing organisations and 1557 representing individuals.

4.5.2 Feature Engineering

We perform feature engineering to describe user profile data based on the textual, numeric and media attributes of the collected Twitter profiles. We consider five different types of features:

- *Syntactic Features*: Syntactic features are based on the assumption that users that belong to the same category may describe themselves using the same type of terminology. For example, organisations generally describe themselves using terms such as business, newspaper, organisation, company, etc. Using the description field of all the users in our training dataset we have generated a word-vector representation for each category: $C_{organisation} = \{w_1, w_2, \dots, w_n\}$, $C_{person} = \{w_1, w_2, \dots, w_m\}$. This vector is generated by tokenizing the terms of the description fields (based on white spaces and punctuation symbols) and by selecting the most frequent terms for the category. The selection of the most frequent terms is based on the analysis of the term frequency distribution for the category. To

assess how syntactically similar the description of a user profile u is to the vocabulary of each of the categories, we extract the word-vector representation of u based on the account's name and description $u = \{w_1, w_2, \dots, w_j\}$ and compute the cosine similarity between the vector representation of u and the vector representation of each of the categories. Syntactic similarity scores from a user profile to all categories are considered as different features for classification.

- *Semantic Features*: Semantic features take into account the entities and types that emerge from the name and description of each Twitter profile u . To extract these entities and types we make use of the TextRazor Natural Language Processing API.¹² For example, for the Twitter account @BarackObama, the semantic annotator recognises entities and concepts such as *Person*, *President*, and *Government Title*. As with syntactic features, semantic features are based on the assumption that users that belong to the same category may describe themselves using the same semantic concepts. Using the description field of all the users in our training dataset, we generated a concept-vector representation for each category: $SC_{organisation} = \{c_1, c_2, \dots, c_n\}$, $SC_{person} = \{c_1, c_2, \dots, c_m\}$. To assess how semantically similar the description of a user profile u is to the semantic description of each of the categories, we extract the semantic-vector representation of u based on the account's name and description $su = \{c_1, c_2, \dots, c_j\}$ and compute the cosine similarity between the semantic vector representation of u and the semantic vector representation of each of the categories. Semantic similarity scores from a user profile to all categories are considered as different features for classification.
- *Network Features*: Network features take into account the position of the user within the network. Network features include: number of followers, number of friends, and number of lists the user is a member of.

¹²<https://www.textrazor.com/>

Table 6: Results of the different classification models

Model	Accuracy	Precision	Recall	F-measure
Naive Bayes	62.38%	0.656	0.621	0.632
SVM	80.55%	0.806	0.805	0.804
J48	77.64%	0.769	0.776	0.764
Log Reg	81.64%	0.827	0.813	0.82

- *Activity Features*: Activity features take into account the actions of the user and how frequently those actions are performed. In particular, we take into account two types of actions: posting and favouring. The first feature, PostRate, represents how many times a user posts per day whether the second, FavouringRate, represents how many times per day the user favours someone else’s content.
- *Avatar Features*: Avatar features take into account the image that the user projects of themselves. The assumption is that organisations are more likely to include an image in their profile, particularly an icon, while a user account representing an individual is more likely to include a profile picture with an image (face) of the individual. The avatar features considered are: (i) DefaultProfile, if true indicates that the user has not set up a Twitter avatar, and (ii) NumFaces. This feature indicates if the profile picture of the user contains a human face. It is computed using the OpenCV image processing library.¹³

The most discriminative features for the categorisation of users are the semantic and network features.

4.5.3 Author Categorisation

Using the feature extractors, we process the 3,283 collected and annotated (company vs. individual) Twitter accounts, and use them to generate different classifiers. In particular, Naive Bayes, Support Vector Machines (SVM), Decision Trees and Logistic Regression have been tested using 10-fold cross validation. The results are displayed in Table 6. The best performing classifier is the Logistic Regression model, obtaining 0.82 F-measure. This generated model is later used in our analysis (see Section 5.2) to filter Twitter accounts belonging to individuals.

5. EXPERIMENTS

We describe here the experiments conducted to analyse the behaviour of the participants of the EH2016, EH2015 and COP21 social media movements, following the proposed approach.

5.1 Data Collection

The first step to perform these experiments was to collect data for the three social media movements: EH2016, EH2015 and COP21. We monitored these events on Twitter by collecting tweets containing particular hashtags, such as #EH16 #EH15, #earthhour, #changeclimatechange, etc. in the case of EH2016 and EH2015, and #COP21, #COP21Paris, #parisclimatetalks, etc. in the case of COP21. We used

¹³<http://opencv.org/>

the Twitter IDs of the participants of these events to generate a second collection and gather historical tweets from their timelines. Up to 3,200 posts were collected from each individual, which is the maximum allowed by the Twitter API. This provides information for up to several years for some users. The rationale behind the selection of these users is that they are already engaged with the environment, as demonstrated by their participating and tweeting about these campaigns, and that the Twitter accounts refer to persons and not to organisations. Our dataset for EH2016 contains 62,153,498 posts from 32,727 users; EH2015 contains 56,531,349 posts from 20,847 users; the one for COP21 contains 48,751,220 posts from 17,127 users.

5.2 User Filtering

As discussed in Section 4.5, it is important to distinguish between different types of social media profiles, particularly organisations vs. individuals. We have therefore used our proposed author categorisation model to filter those accounts that represent organisations from our previously collected datasets. Our results show that 17% of user accounts participating in EH2016 belong to organisations, 15% for EH2015 and 24% in the case of COP21. After filtering the identified accounts and their corresponding posts we remain with 27,163 users and 44,367,133 posts for EH2016, 17,719 users and 39,267,884 posts for EH2015, and 13,016 users and 28,200,780 posts for COP21. Note that the post reduction for each dataset is higher than the user reduction, since the organisations filtered from the datasets (EH, WWF, Greenpeace, etc.) tend to broadcast a high number of posts.

5.3 Data Filtering

We collected 3,200 posts from the timelines of each of the users who participated in the social media movements. Naturally, these users post about environmental issues, but they also post about their jobs, hobbies, personal experiences, and so on. To identify which of the content produced by the users relates to their environmental behaviour, we used the Term Extraction tool ClimaTerm¹⁴ developed in the context of this research and documented in [22]. ClimaTerm automatically identifies instances of environmental terms in text. Some of these are found directly in ontologies such as GEMET, Reegle and DBpedia, while others are found (using linguistic techniques) as variants of such terms (e.g. alternative labels, or hyponyms of known terms) [22]. Using these annotations helps us to identify, from the timeline of each individual user, which of their posts are related to climate change and sustainability. 658,140 posts were identified as climate-related by the ClimaTerm tool in the EH2016 dataset, 447,892 posts in the EH2015 dataset, and 250,215 in the case of COP21.

5.4 Behaviour Analysis

We have made use of the filtered tweets to categorise users in different behavioural stages over time. In particular, we take into account monthly behaviour before, during and after the days in which EH2016, EH2015 and COP21 were celebrated. We focused on the analysis of these particular months, since being aware of the users’ behavioural categorisation during these time periods may enable campaigners to use more targeted messages and interventions. The results

¹⁴<http://services.gate.ac.uk/decarbonet/term-recognition/>

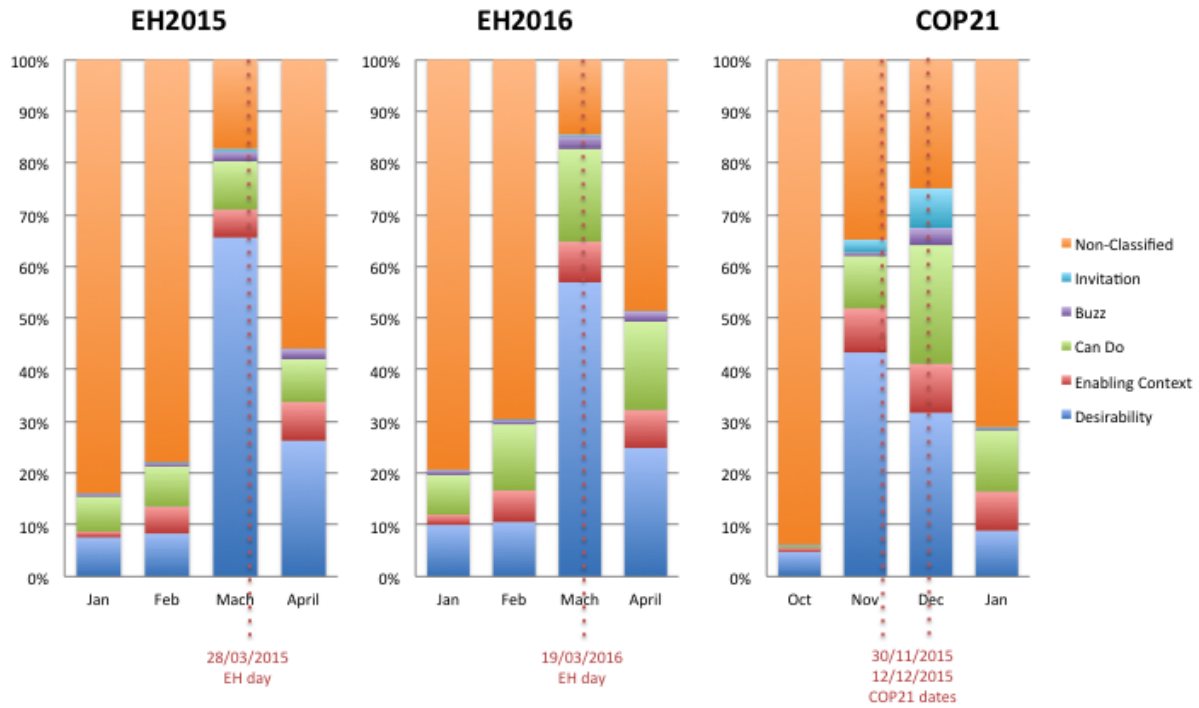


Figure 3: EH2015, EH2016, COP21 - Number of users associated with each behavioural category

Table 7: Behaviour Analysis results

EH2016	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
Jan	2711	543	2087	234	33	21,555
Feb	2871	1654	3476	221	42	18,899
Mach	15456	2135	4879	658	99	3,936
April	6754	2003	4632	544	21	13,209
EH2015	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
Jan	1344	199	1201	88	20	14,867
Feb	1476	924	1378	121	22	13,798
Mach	11621	956	1655	332	100	3,055
April	4657	1324	1465	350	17	9,906
COP21	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
October	621	98	57	15	12	12,213
November	5640	1112	1321	88	321	4,534
December	4124	1234	2987	432	998	3,241
January	1156	987	1543	44	34	9,252

of our behaviour analysis study are presented in Figure 3 for EH2015, EH2016, and COP21. These images display the percentage of users classified under each behavioural stage in the months around the campaigns, as well as the users that are not categorised. Users are not categorised either because they did not produce any posts related to environmental issues in the analysed month, or because our approach could not distinguish a clear stage for the user based on their generated content. The number of users in each stage for the three datasets is reported in Table 5.3.

As we can see from these figures, there is a significant peak of activity around the time of the campaigns that decays later on. During the time of the campaigns, users produce more content related to environmental issues and it is therefore possible to classify them in different behavioural stages. Out of this time window, a higher percentage of users goes uncategorised, mainly because they have not produced any content around environmental issues. In general, what we observe from all campaigns is that the highest percentage of users are in the Desirability stage. The second most popular stage is Can do. This indicates that users are either at the stage where they want to change their behaviour, or at the stage where they are already acting. An interesting observation, particularly between the EH2016 and EH2015 results is that in 2016 there is a high percentage of users in the Can do stage vs. the Desirability stage, which may indicate a successful evolution in the environmental behaviour adopted by users.

Not many users, however, fall in the invitation or buzz stages, i.e., not many users are trying to engage others. As analysed in our previous work [16], during the EH campaigns, messages reflecting buzz and invitation stages tend to come from environmental organisations such as WWF or Earth Hour. This changes slightly for the COP21 movement, where a subset of users are actively inviting others to put pressure on their Governments so that they keep meeting climate change commitments. The percentage of users at the enabling context state is generally stable, but as with the Can do stage, this percentage is also slightly higher for EH2016 than for EH2015, indicating a behavioural evolution and a higher interest for learning about climate change and the environment.

What do these results teach us, and how can we use these learnings for further campaign improvements? We summarise the results of studying behaviour in these three campaigns and our previous learnings from our literature review in three additional recommendations:

- Our results show that most of the social media participants are at the desirability stage. There is something they want to change but they do not know how. A big part of a campaign's effort should therefore be concentrated on providing messages with very concrete suggestions on climate change actions. These messages should also be innovative, useful, and about day to day activities to maximise the STEPPS criteria [6].
- There are very few individuals in the invitation stage. Most invitation messages during these campaigns are posted by organisations, although this seems to change with the type of social media movement. A social media movement, such as COP21, which is more oriented to act and change policy, involves more users in the invitation stage, who aim to attract others to their cause.

However, as stated by Robinson [26], for an invitation to be effective, it is vital who issues the invitation. Ideal inviters are those who have embraced change in their own lives and can serve as role models. It is our recommendation to identify these really engaged individuals and community leaders and involve them more closely in the campaigns, invite them to share their stories, and provide feedback, so that they can inspire others. In addition, as reflected by Proskurnia [25], the more connected these individuals are in the network, the higher the level of engagement they can potentially generate

- Communication in our collected data generally functions as broadcasting, or one-way communication, from the organisations to the public. However, frequent and focused feedback is an intervention strategy that can help build self-efficacy and nudge the users in the can do and buzz stages in the direction of change. Our recommendation for campaigners is therefore to dedicate efforts towards engaging in discussions and providing direct feedback to users.

6. DISCUSSION

Engaging people with climate change by using social media as a medium not only requires the understanding of how social media communication can drive engagement and behaviour change, but also requires the understanding of the needs and situations of the users so that more targeted strategies can be selected to drive such change.

In this work, we have investigated how the combination of theories and computational models can help us to identify and categorise the behaviour of users towards the environment and to select more targeted communication and intervention strategies. This work has provided us with many useful insights. In this section we highlight some limitations of this study and multiple directions for future work.

Social media behaviour is not exactly the same as behaviour in the physical world. People do not report everything they do and how they do it via social media. While the results of our conducted questionnaire (see Section 4.1) indicate an association between behavioural stages and different types of communication, our learnings about users' behaviour from their generated content may be only a partial reflection of the reality. Previous studies indicate that variances may exist between self-reported behaviour and objective, or real behaviour [21]; for example, people tend to report themselves as being more environmentally friendly than they really are.

Our classifier was trained with a small subset of tweets because of the cost of obtaining labelled data. Classification accuracy (71.2%) may therefore improve by using more training data. Adding some extra linguistic features, such as the recognition of numeric facts or expressions of need, could also potentially help to enhance classification accuracy. We are currently working on extending the GATE NLP tools to extract additional features that can provide a more complete characterisation of the data.

Our classifier has been trained on Twitter data, which has a maximum of 140 characters per post. The length of the text may therefore determine the number of directives or emotions that emerge from one unique post. While our proposed analysis approach is generic and can be ap-

plied to analyse data from any given social media platform, our classifier is Twitter-specific and may need to be re-trained to work with longer texts. In addition, it is important to highlight that users may express their message differently in different social networking platforms, and that behavioural stages may be communicated differently, or certain behavioural stages may be more prominent in some platforms than in other ones. A natural extension of this work should therefore be to compare the results of from Twitter with results from other platforms, or even to offline-campaigns. In a similar way, while the proposed methodology can be applied to analyse smaller and more localised campaigns, further research is needed to assess whether the same findings emerge from smaller environmental campaigns.

To analyse behaviour, we have considered a unique time-window of one month for all users. During a month time users may post messages that belong to different behavioural stages. Our approach has been to assign to the user the most popular behaviour stage among their posts. However, more advance approaches that consider the distribution of posts during the time period (i.e., the user's behavioural variance) can also be explored. In addition, it is important to highlight that different users post at different paces. Our future work includes studying the impact of users' post rate for a more fine-grained categorisation of behaviour.

While our analysis of the COP21 and EH movements distinguishes between different types of social media profiles (organisations vs. individuals), our approach has focused on the identification of three different types of organisations (News Agencies, NGOs, and Companies), which are largely involved in these campaigns. However, other types of organisations, such as those related to banking, medical, or other more specific sectors have not been included in our training data and may therefore not be recognised by our classifier.

In addition to the identification of individuals vs. organisations, a future extension of our work will consider researching automatic methods for the identification of communities and community leaders during these campaigns. At the moment, environmental organisations, such as WWF, identify these community leaders empirically, by observing the active and engaging individuals towards the organisation and its social media communications. Our future work will investigate how current works, e.g. [9] [3], can be adapted to the domain of environmental campaigns in order to expand our user categorisation model to identify influential users and their specific behaviour.

While our work has focused on recommending social media campaigns to make them more effective towards the public, a possible extension of our work is the analysis of campaigns to pressure government and create policy change, particularly by studying the effects of online petitions. In [19], Hale and colleagues study petition growth and success rates for more than 8,000 petitions in the UK and highlight key characteristics of successful petitions in terms of fluctuations and growth, providing key insights on the design of these petitions and the campaigns behind them. In the concrete case of environmental campaigns Proskurnia and colleagues [24] analysed over 100 environmental campaigns and highlighted that, while there is no clear distinction between campaigns in terms of successful petitions, petitions should be particularly considered in the context of mobilisation campaigns. Our future work will consider a more exhaustive analysis of petitions as a form of intervention to

promote behaviour change and how the achieved behaviour change influences the success of petitions.

Finally, it is important to highlight that little is known about the long-term effects of interventions. It is unclear whether behavioural changes were maintained and whether new habits were formed, or if they returned to the baseline. While our study is currently purely observational, long-term empirical studies are needed to better assess the effect of interventions, particularly within social media.

7. CONCLUSIONS

Pursuing awareness and changes in behaviour, governments and organisations are constantly conducting pro-environmental campaigns. However, little knowledge has been built around connecting social media and its potential to boost behaviour change. Following this goal, we have presented in this paper: (i) a deep state of the art analysis on the different theoretical perspectives towards increasing awareness, engagement and behaviour change; (ii) a computational analysis approach, inspired by the 5 Doors Theory [26], to automatically identify users' behavioural stages, and its use for analysing three of the largest and more recent environmental social media movements (EH2016, EH2015 and COP21); and (iii) the combination of the lessons learned from theories and data analysis to provide a series of recommendations on how to enhance social media campaign communication.

Acknowledgments. This research is part of the project DecarboNet, funded by the FP7 program of the European Union, grant agreement 610829.

8. REFERENCES

- [1] W. Abrahamse, L. Steg, C. Vlek, and T. Rothengatter. A review of intervention studies aimed at household energy conservation. *Journal of environmental psychology*, 25(3):273–291, 2005.
- [2] E. Amigó, J. Carrillo-de Albornoz, I. Chugur, A. Corujo, J. Gonzalo, E. Meij, M. de Rijke, and D. Spina. Overview of replab 2014: author profiling and reputation dimensions for online reputation management. In *International Conference of the Cross-Language Evaluation Forum for European Languages*, pages 307–322. Springer, 2014.
- [3] S. Aral and D. Walker. Identifying influential and susceptible members of social networks. *Science*, 337(6092):337–341, 2012.
- [4] D. Ariely. *Defining Key Behaviours*. 2014.
- [5] D. Ariely, J. Hreha, and K. Berman. *Hacking Human Nature for Good: A Practical Guide to Changing Human Behavior*. 2014.
- [6] J. Berger. *Defining Key Behaviours*. 2013.
- [7] H. Blunck. Computational environmental ethnography: combining collective sensing and ethnographic inquiries to advance means for reducing environmental footprints. In *Proceedings of the fourth international conference on Future energy systems*, pages 87–98. ACM, 2013.
- [8] A. Campbell. *How cavemen did social media. A comparative case study of social movement organisations using Twitter to mobilise on climate change*. PhD thesis, The University of Sydney, 2010.

- [9] M. Cha, H. Haddadi, F. Benevenuto, and P. K. Gummadi. Measuring user influence in twitter: The million follower fallacy. *Icwsn*, 10(10-17):30, 2010.
- [10] M. Cheong and V. Lee. Twittering for earth: A study on the impact of microblogging activism on earth hour 2009 in australia. In *Intelligent Information and Database Systems*, pages 114–123. Springer, 2010.
- [11] A. Corner, E. Markowitz, and N. Pidgeon. Public engagement with climate change: the role of human values. *Wiley Interdisciplinary Reviews: Climate Change*, 5(3):411–422, 2014.
- [12] H. Cunningham. GATE, a General Architecture for Text Engineering. *Computers and the Humanities*, 36:223–254, 2002.
- [13] A. Darnton. Behaviour change knowledge review–reference report. *Andrew Darnton for the Government Social Research Unit*, 2008.
- [14] N. Eyal. *Hooked: How to build habit-forming products*. Penguin Canada, 2014.
- [15] M. Fernandez, G. Burel, H. Alani, L. S. G. Piccolo, C. Meili, and R. Hess. Analysing engagement towards the 2014 earth hour campaign in twitter. 2015.
- [16] M. Fernandez, L. S. Piccolo, D. Maynard, M. Wippoo, C. Meili, and H. Alani. Talking climate change via social media: communication, engagement and behaviour. In *Proceedings of the 8th ACM Conference on Web Science*, pages 85–94. ACM, 2016.
- [17] B. J. Fogg, 2003. <http://www.behaviormodel.org/>.
- [18] J. Froehlich, L. Findlater, and J. Landay. The design of eco-feedback technology. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1999–2008. ACM, 2010.
- [19] S. A. Hale, H. Margetts, and T. Yasseri. Petition growth and success rates on the uk no. 10 Downing street website. In *Proceedings of the 5th annual ACM web science conference*, pages 132–138. ACM, 2013.
- [20] E. Kazakova. Environmental campaign construction and symbolism. 2009.
- [21] C. Kormos and R. Gifford. The validity of self-report measures of proenvironmental behavior: A meta-analytic review. *Journal of Environmental Psychology*, 40:359–371, 2014.
- [22] D. Maynard and K. Bontcheva. Understanding climate change tweets: an open source toolkit for social media. In *Proceedings of EnviroInfo*, Copenhagen, Denmark, 2015.
- [23] L. S. Piccolo and H. Alani. Perceptions and behaviour towards climate change and energy savings. Copenhagen, Denmark, 2015. EnviroInfo and ICT4S 2015: Building the Knowledge Base for Environmental Action and Sustainability.
- [24] J. Proskurnia, K. Aberer, and P. Cudré-Mauroux. Please sign to save...: How online environmental petitions succeed. In *Workshop Proceedings of the 10th International AAAI Conference on Web and Social Media*, number EPFL-CONF-218073. AAAI Press, 2016.
- [25] J. Proskurnia, R. Mavlyutov, R. Prokofyev, K. Aberer, and P. Cudré-Mauroux. Analyzing large-scale public campaigns on twitter. In *International Conference on Social Informatics*, pages 225–243. Springer, 2016.
- [26] L. Robinson. Doors. an integrated theory of behaviour change. 5.
- [27] E. M. Rogers. Elements of diffusion. *Diffusion of innovations*, 5:1–38, 2003.
- [28] Science and T. Committee. Communicating climate change. Technical report, House of Commons, 2014. <http://www.publications.parliament.uk/pa/cm201314/cmselect/cmsctech/254/254.pdf>.
- [29] C. Shaw, A. Corner, J. Clarke, and O. Roberts. Are we engaged? un climate talks and the uk public. Technical report, Climate Outreach, 2015.
- [30] G. Vaynerchuk. *Jab, Jab, Jab, Right Hook*. Harper Collins, 2013.
- [31] L. Whitmarsh, I. Lorenzoni, and S. O’Neill. *Engaging the public with climate change: Behaviour change and communication*. Routledge, 2012.