EC Project 610829

A Decarbonisation Platform for Citizen Empowerment and Translating

Collective Awareness into Behavioural Change

D4.2: Algorithms for Categorising and Predicting User Behaviour

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Version history

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Executive Summary

This deliverable summarises the efforts of the DecarboNet project on identifying and analysing user behaviour towards the environment. Our approach for analysing behaviour is based on the 5 door theory of behaviour change. This theory defines 5 different stages that users adopt in a behaviour change cycle, from *desirability*, when they start being aware of the problem, till *invitation*, when they are completely engaged with the cause and try to engage others.

Focusing on this theory we have developed a general behaviour analysis methodology to identify the different behavioural stages in which users are based on their use of social technology. In particular we have selected Twitter, a popular microblogging platform, and the Climate Challenge, a game with a purpose developed within the context of DecarboNet, for this investigation.

By using our proposed methodology we have analysed the behaviour of 20,847 twitter users and 442 participants of the Climate Challenge game. The results of our analysis reveal that behavioural stages can be successfully identified by considering a variety of linguistic features (as in the case of Twitter), and a variety of interaction features (as in the case of the Climate Challenge).

The goal of tracking these behavioural stages is to (a) understand existing behaviour change dynamics, and (b) identify, and promote, specific actions and interactions to nudge behaviour towards pro-environmental engagement.

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1. Introduction

Despite all the investments in technical innovations to reduce carbon emissions, behaviour change is still considered a central strategy to mitigate climate change [EEA, 2013; Moore, 2012]. Promoting a behaviour change towards protecting the environment is a complex mission, since individuals do not always respond rationally to favourable economic or more sustainable choices [Moore, 2012]. Different sociocultural forces (or barriers) such as personal values, incentives, formal support, peer pressure, also influence behaviour. In this context technology can play different roles in the challenging task of leveraging behaviour change.

In particular, social media platforms can expand the potential of technology to nudge behaviour change from the individual level to the collective, thus boosting a positive social change. By enabling dialogue and quick information diffusion, social media could help shaping opinions and disseminating patterns of behaviour; a potential catalytic power in engaging people with a social issue such as climate change [Shirky, 2011; Kamal, 2013].

In this deliverable we present our developed behaviour analysis models, used to analyse the behaviour of 20,847 twitter users and 442 participants of the Climate Challenge game (D3.1). Twitter users were selected by considering their participation in the 2015 Earth Hour (EH) campaign. EH is a campaign launched yearly by they World Wide Fund for Nature (WWF) in which individuals and organisations are requested to switch off the lights for one hour as a symbolic action to raise awareness about climate change. By analysing the timeline of EH participants our goal is to understand and identify the different stages in which users are with respect to their behaviour towards the environment.

Our developed behaviour analysis models are grounded on the 5 door theory of behaviour change [Robinson, 2011]. This theory states that, in a cycle of behaviour change users pass by 5 main stages, from *desirability*, when users start being aware of the problem, till *invitation*, when users are involved engaged with the cause and invite others to follow their steps and change their behaviour.

To automatically identify these 5 behaviour stages our behaviour analysis models make use of linguistic features, such as the sentiment, emotions or directives expressed by the users within their social media posts. To extract these linguistic features, our models make use of the Natural Language Processing (NLP) tools developed by WP2. These novel set of features have

been incorporated into our semantic model (see D4.1) to provide a more fine-grained representation of the users and their context

We have also extended our behaviour analysis model to understand the different behavioural stages in which users are based on their participation in Climate Challenge. Climate Challenge is an online competition in the tradition of games with a purpose designed to increase environmental literacy and motivate users to adopt more sustainable lifestyles. To automatically identify the users' behavioural stages within this game, several behavioural features have been extracted based on the users' participation in pledges and on their knowledge about the environment.

2. State of the Art

In this section we provide a brief summary of the state of the art on behaviour change from a social and technological perspective, with a particular focus on behaviour change towards the environment. In particular, we present in this section the 5-door theory of behaviour change, a general theory that constitutes the base of our developed behaviour analysis models.

2.1. Understanding Behaviour Change

Different scientific domains such as psychology, anthropology, sociology, and philosophy have put effort into understanding the forces that drive people's behaviour and decisions for engagement with protecting the natural environment [Blunck et al., 2013; Corner et al., 2014]. This "*not emotionally neutral subject*" [House of Commons, 2014] 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.

Behavioural change theory is mainly dominated by two complementary approaches: models of behaviour and theories of change.

Socio-psychological **models of behaviour** can be applied to understand specific behaviour and to identify factors of influence, mainly at the individual level [Darnton, 2008]. The majority of behaviour-change oriented research in technology design is based on an individual model and, according to Hekler et al. [Hekler et al., 2013] not considering the context in which a technology will be used.

Theories of change explain the behaviour change process through social science lenses, being particularly helpful to develop interventions leading to a desired behaviour change. For this reason, they have been applied to policy

making aiming at promoting social changes [Darnton, 2008]. Theories are generic, not taking into account contexts, perceptions and needs of a particular group of people [Robinson, 2011]. Nevertheless, balancing abstraction with contextual relevance is needed [Hekler, 2013]. Selecting then the best theory or model from hundreds of different conceptual views to inform technological design can be a challenging task [Darnton, 2008].

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 Door Theory [Robinson, 2011]. This generic theory aggregates elements from Diffusion of Innovations [Rogers, 2003] and the Self-Determination Theory of motivation,[1] among others. Instead of promoting changes to people's beliefs or attitudes, the 5 Door theory focuses more on "*enabling relationships between people and modifying technological and social contexts*". This theory consists of 5 behavioural stages that must be present in a cycle of behaviour change. Figure 1 illustrates these behavioural stages:

1. *Desirability*: take into account people desire, the need for change
2. *Enabling context*: modify the social and technological context to enable action
3. *Can do*: build actor's self-efficacy
4. *Buzz*: generate positive buzz, interest
5. *Invitation*: frame an emotionally compelling invitation

[1] https://en.wikipedia.org/wiki/Self-determination_theory

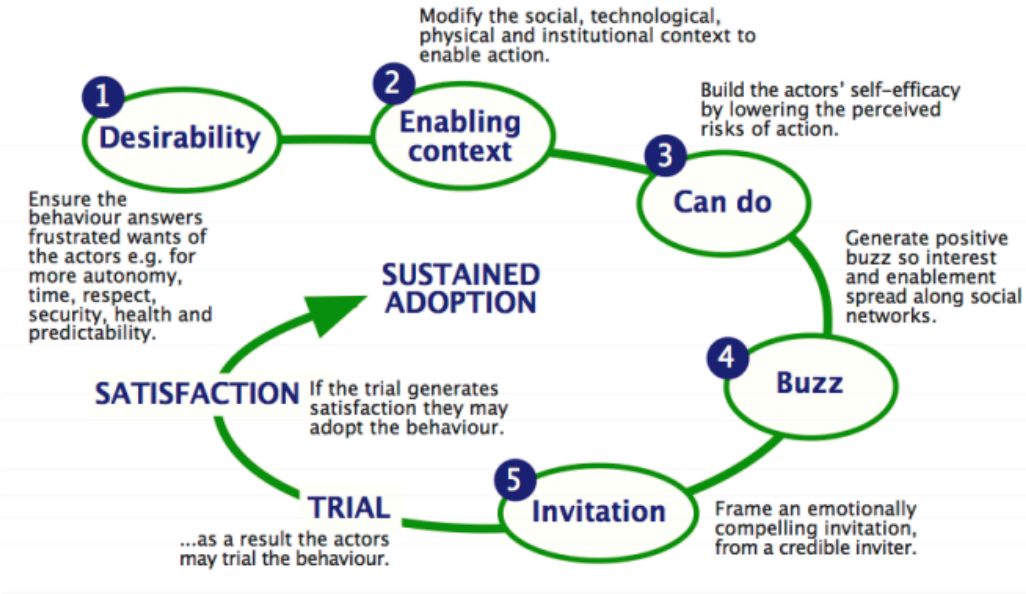


Figure 1 – Five Doors Theory of Behaviour Change

Knowing the different behavioural stages in which a user is can help to determine the type of intervention strategies that are more adequate in order to trigger a behavioural evolution. For [Darnton, 2008], interventions should be informed by theory and developed on the ground. In the next section we describe some of the technologies that intend to promote behaviour change focusing on energy saving as the desired behaviour.

2.2. Behaviour Change Towards Energy Conservation

Assuming that individuals, at different stages of behaviour change, may require different informative support, He et al. [He et al., 2010] relied on the Transtheoretical Model [0], a behaviour model, to design energy consumption feedback.

Although the individual approach is dominant in technology design for promoting [Pierce et al., 2012], some authors [Dourish et al., 2010] argue that environmental issues should not be turned as personal moral choices only. The social context is important to be considered not only to make changes more effective, but also to promote changes in larger scale, influencing policymaking.

Associating social media to technology to leverage behaviour change can actually bring context and social connections to promote behaviour. For the Climate Change Communication Advisory Group [Advisory Group, 2010],

"*there are few influences more powerful than an individual's social network*", to promote more environmentally friendly behaviour.

The potential of social media to disseminate and to incite pro-environmental behaviour was explored by [Zita et al., 2014] among staff members in an educational institution, recognising Facebook as an effective tool in that context. In [Defra, 2010], the authors found that being part of a collective effort was considered more important to the participants than the effectiveness of the action on the environment, reinforcing the importance of connecting people for collective efforts.

In terms of energy savings, engaging people with the issue has been proven to be a complex task [EEA, 2013][Darnton, 2008], since energy is out of sight and usually out of mind [Hargreaves et al., 2010]. In general, people do not wish to be profligate and to waste energy: many *do* have a carbon conscience, however latent. Again, connecting people to find solutions together and disseminate it has been shown to be a promising approach.

Following this idea, as part of DecarboNet we evaluated an online debate tool as a favourable approach to motivate engagement and to raise energy awareness in a collective way in a workplace [Piccolo et al., 2014]. The possibility to interact with other people's ideas (adding arguments or even voting) was considered the main motivational aspect to engage participants.

Initiatives such as [Foster, 2010], [Petkov et al., 2011], Welectricity[2] and Opower[3] are also based on social network to foster energy savings. EnergyWiz. [Petkov et al., 2011] explored social comparison one-on-one and ranking to motivate savings. This project also relies on environmental psychology to design tailored eco-feedback considering different values (altruistic, egoistic, and biospheric) related to environmental concerns [Petkov et al., 2012].

Although the number of new developments targeting has increased in the last years [Hekler, 2013], a better understanding of the factors that influence people's behaviour towards energy conservation is still necessary [Dillahunt et al., 2014] In the same extent, it is still required to learn how to best explore the potential of technology to create awareness of problems and possible solutions requesting collective efforts.[4]

In the next sections we present our proposed approach to analyse behaviour towards the environment based on the users' participation in various social

[2] http://welectricity.com/
[3] https://social.opower.com
[4] http://caps2020.eu

contexts (including a social media platform, Twitter, and a game with a purpose, Climate Challenge). Our goal is to provide a step towards the understanding of the factors that describe people's behaviour towards energy conservation within a social context. Our behaviour analysis methods explore multiple linguistic and interaction features, and identify which features are more distinctive to automatically identify the users' behavioural stages within the cycle of behaviour change [Robinson, 2011]. The automatic identification of these stages can enable a more targeted application of intervention strategies.

3. Analysing Behaviour in Twitter

In this section we describe our approach to automatically identify the different behavioural stages in which users are, following the 5-door theory of behaviour change [Robinson, 2011].

3.1. Data Collection

To conduct this research we collected 56,531,349 posts from 20,847 users, all of them participants of the Earth Hour 2015 campaign. Earth Hour is a global campaign launched by the World Wide Fund for Nature (WWF) every year, with the purpose of raising awareness about climate change and sustainability issues. Every March, Earth Hour celebrates the symbolic "lights off" hour, which has grown from a one-city initiative to a mass global event involving more than 162 countries and 7,000 cities and towns.

By monitoring the event and its participants in Twitter we collected more than 20K social media profiles. We then crawled the timeline of all these users up to the latest 3,200 posts per user, which is the maximum allowed by the Twitter API. Specific data collectors were developed for this purpose. The rationale behind the selection of these users is that they are users already engaged with the environment, as they demonstrate by participating and tweeting about the campaign.

3.2. Manual Annotation of Tweets

When a user participates in a social media platform, such as Twitter, there are multiple behaviour dimensions that can be studied to monitor her behaviour (popularity, engagement, contribution, etc.). In D4.1 we specified a series of behaviour dimensions identified in the literature of social media analysis and develop a semantic model to represent users' behaviour based on these dimensions.

In this work, we aim to provide a step forward by automatically identifying the users' behaviour towards a specific topic of interest, in this case behaviour towards the environment. To perform our analysis we need to dig deeper into the content posted by the users and try to understand: (i) which of that content does actually relate with their behaviour towards the environment and (ii) how can we identify their particular level of compromise towards the environment by analysing such content (i.e., how can we identify the behavioural stage in which a user is based on his social media contributions).

In order to understand what are the distinctive characteristics of the language used by the users in each behavioural stage, a set of 100 tweets was manually categorised by two different researchers. Discussions were raised about those tweets where disagreements were found. If the disagreement could not be resolved, the tweet is marked as ambiguous; otherwise, the tweet is marked as belonging to one of the 5 different behavioural stages (desirability, enabling context, can do, buzz or invitation). Examples of the annotated tweets are listed below. The complete dataset of annotations can be found under:

Tweets annotated as representing the *Desirability* stage
Gore compares carbon emissions to the subprime morgage crisis...need to deal with climate crisis now because we won't be able to bail it out
RT @Worldchanging When Should We Take Action on Climate Change? http://tinyurl.com/c9vjyy
It was sucha horrible storm today! Doesnt feel like the normal rain that we are used too isnt it?! Climate change?
Its sad that we are in a unifing global race against climate change but US has not laced up yet
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.
No climate-change deal likely by year's end, officials say - not good - http://tinyurl.com/y879388
Where can we go in America to get beat up by police while protesting for climate chat? Copenhagen is too far - http://nyti.ms/8D2VzS
What lighting offers the greatest energy savings? OUr experts explain.

#Title24 http://t.co/75ys9IYvza #EatonEngaged http://t.co/R1e8vRG0f3
Tonight is the annual night I needlessly expend energy by getting wound up at how fucking POINTLESS #earthhour is...
First they tell you to turn off your lights for Earth Hour and then they blame you running over 200 people. Heh idiots

https://docs.google.com/spreadsheets/d/1EFW_OSxbtXd2QttnWJHeu7dP43gOYeTuN7w7Dw62jFQ/edit?usp=sharing

Desirability – satisfying a need

For someone to adopt a new behaviour into their lives, they have to want it. A good way to understand desire is that it is driven by frustration. People are motivated to reduce their frustrations, which can be about day-to-day inconveniences (e.g. bicycling to work to avoid traffic), or about deeper personal frustrations that challenge people's identities (e.g. cycling to recover lost health or fitness).

Enabling context – changing the environment to enable the behaviour

In planning a change program the actors' entire contextual system therefore needs to be open to analysis and, potentially, modification. That includes infrastructure, services, social norms, social organisation, leadership, technology, pricing, regulation, governance – literally anything that could exert a positive or negative influence on a specific behaviour.

Tweets annotated as representing the *Enabling Context* stage
Changing a light bulb. Compact Fluorescent Lights last longer, use less energy, and save you money. Answer the Call at liveearth.org.
Europe Pledges Billions in Climate Aid for Poor Nations - http://bit.ly/8BVbtb
Cold air hand dryers utilise high air speed to dry hands quickly, helping to provide ongoing energy savings: http://t.co/8Ssq1aa6xs
The benefits of solar photovoltaics extend to long-term energy savings: http://t.co/JOEpSdiINF
EU sets 'ambitious but realistic' energy savings target http://t.co/1wmWiBHfCA
$18 Trillion Windfall: Health And Productivity Benefits of Efficiency Top Energy Savings http://t.co/vvHoOlcoiR

$250 BILLION US #Energy Savings in Shift to LED lighting by 2030: According to DOE #ClimateHope http://t.co/efS6zoTb9O
Make sure to only charge your phone when it has reached a low battery level to save energy! #YourPowerUAE #EarthHour http://t.co/MgwI6fRCrl

Can do – increasing the actors' self-efficacy

Self-efficacy is built at the level of tactics. Tactics that can grow people's self-efficacy (and lower the perceived risks of change)

Tweets annotated as representing the *Can Do* stage
Flipping the switch. Always turn off the lights when leaving a room. It uses less energy than leaving them on. Learn more at liveearth.org.
Energy Action final hours need to stay in 1st place to win $200k to combat climate change. Please vote http://tinyurl.com/cz2z26
UN Campaign on Climate Change - sign the petition to Seal the Deal at Copenhagen http://www.sealthedeal2009.org #cop15
Look for the chance to submit ideas for the Climate Action Plan in Jan! #GWSustain
Please help the world', COP15 opening video now on YouTube http://bit.ly/56WESq #copenhagen #climate (via @cop15)
Live greener at home: Optimize your water heater, optimize your energy savings! http://t.co/jQu7Wa4frV http://t.co/7cD8qyfDHC
Track your energy savings with this student-developed website #macewanu #yeggreen http://t.co/jckR9XAFKu http://t.co/2V2wEFkqg1
Give the gift of light to the children of the Philippines. Support WWF projects w/ #EarthHour! http://t.co/TdCjXo5lN1 http://t.co/tTfQB0KGcS
How to make our night sky more beautiful: Attend the Earth Hour Celebration https://t.co/kXpCqBOIso #DeLightPGH #EarthHourPGH @go_gba
YOU have the power to make the celebration of Earth Hour more meaningful, beyond the 60-minute lights-off. http://t.co/tdk49qC6sZ
Turn off your lights for #EarthHour on March 28, 2015 from 8:30pm to 9:30pm http://t.co/2TdrU4v3Qp

Positive buzz – having a story that prepares people to act

Nothing happens without conversation. Conversation, or at least interaction, carries change along social networks. It connects people, determines social norms, and it's how societies and groups make choices. Conversation is the key to culture change, since a group's culture is the sum of its conversations.

Tweets annotated as representing the *Positive Buzz* stage
Filling my tires and saving one tank of gas per year! Climate Crisis Solution #06 @ www.liveearth.org
Climate change with Gov. Schwarzenegger http://bit.ly/5CZA7b
#IoE in our cities increasing energy savings by 30%, reducing water consumption 50%, lowering crime rates @WimElfrink http://t.co/X9zWvnrjHo
RT @KHayhoe: 'We thought we'd achieve 10% energy savings thru efficiency. We were SO WRONG. It's 40%--so far.' Wendell Brase, UC-Irvine #Mo…
I support sustainable fishing with @MSCintheUK & @wwf_uk I challenge @m_jouat @SWFPA @buchanjimmy #FishFace EarthHour http://t.co/4lnT1vvb64
Hammad Naqi Khan, DG, WWF-Pakistan talks about the importance of the #EarthHour http://t.co/SykAY5ssnj
Proud to be the Brand ambassador of WWF's Earth Hour. 2015. Cycled on the wide streets of Delhi early morning. http://t.co/js90TS6vhH
We are revealing the stars during Earth Hour- and the weather looks fine! #Earthhour @maas.museum https://t.co/iXZ2I63I1O
Did you know we only use recycled carpet, tile and stone @MondrianLDN ?#didyouknow @earthhour @wwf_uk #earthhour

Invitation

Change is a little like a dinner party. Even when people want to come, they still need an invitation. Who issues the invitation is vital. An inviter should be passionate, similar, connected and respected. A good inviter wins people's attention and commitment by authentically modelling the change in their own lives.

Tweets annotated as representing the *Invitation* stage
Have you seen climate change? Tell us about it!
check out @350's beautiful new video about the global climate movement. Please pass it on! http://is.gd/14C23 #350ppm
join us! RT @ning: It's all about stopping climate change at @LiveEarth's Friends of Live Earth http://bit.ly/5fjwq
Join the party today at 2:00 PM ET. Learn more about our energy savings products. #ENERGYSTARPOY #EatonEngaged http://t.co/EROrjoWjHu
We hope you're all participating in Earth Hour tonight! It starts at 8:30!!! http://t.co/2VI8xxo2IA
Join us at the Earth Hour Acoustic Concert on March 28th at the Ranny Williams Entertainment Centre. #EarthHourJA ' http://t.co/vfRM2Xdpkk
Hi Guys, Join me for Earth Hour 2015. Log onto http://t.co/5ixnYqILur http://t.co/a4kIqt1YIo
Show Your Commitment and Join our Earth Hour Challenge! #YourPower

#PoweredbyNature #Londolozi http://t.co/4aAQS6bgjR http://t.co/oS5AanpZ7G
I'm switching off for Earth Hour at 8.30pm on 28 March, will you join me? #EarthHourUK http://t.co/eitii1ojqW
We're participating in the Earth Hour by turning our lights down and encouraging energy conservation. Are you? #EarthHour

3.3. 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 several linguistic patterns were identified as useful linguistic features to 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.
    - Negative sentiment (expressing personal frustration – anger / sadness)
    - URLs (generally associated with facts)
    - Questions (how can I? / what should I?)
- **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.
    - Neutral
    - Conditional sentences (if you do [..] then […])
    - Numeric facts [consumption/pollution] + URL
- **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)

  - Neutral sentiment
  - Orders and suggestions (I/you should/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.
  - Positive sentiment (happiness / joy)
  - (I/we + present tense) I am doing / we are doing
- **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 generally contains vocative forms (friends, guys) calling others to join the cause.
  - Positive sentiment (happy / cute)
  - [vocative] Friends, guys
  - Join me / tell us / with me

3.4. Feature Engineering

Once the prominent characteristics of each behavioural stage were identified by performing a manual inspection of the annotated tweets, the complete collection of EH tweets was processed with different NLP applications in order to produce features that could be used as the basis for distinguishing: (i) which of the content produced by the users relates to their behaviour towards the environment and, (ii) how can the different behavioural stages in which a user is can be automatically identify from such content.

As mentioned in the previous section, for example, tweets that contain strong positive sentiment about environmental issues typically indicate high engagement (stages 4-5 in the behaviour model of the 5 doors theory of change [Robinson, 2011]). It is not just about sentiment, however; many other linguistic features can be used. For example, tweets containing questions about how to solve problems, benefits etc. might be correlated with stage 1 in the model (Desirability).

To identify which of the content produced by the users as part of their social media contributions relates to their behaviour towards the environment we

used the Term Extraction tool ClimaTerm developed in WP2 and documented in D2.2.1. This tool automatically extracts environmental terms from text. Most of these terms are found in ontologies such as GEMET, Reegle and DBpedia, though some are also identified as related terms (e.g. alternative labels, or hyponyms of existing terms). Using these annotations help us to identify, from the timeline of each individual user, which of his/her posts are related to climate change and sustainability.

One issue that we encountered by using these dictionaries is that there are many terms that are relevant in an environmental context (i.e. if we know the tweet is already about something to do with the environment). However, many of these terms are either ambiguous or simply not relevant when the tweet is not about the environment. For example, “bacteria” could be very relevant when talking about the environment, but less so when talking about hospitals. This is particularly the case for the terms found in GEMET (the Reegle terms are much more specific).

To enhance the accuracy of our identification method we consider that a tweet talks about environmental issues if at least two terms are identified or if at least two out of the four dictionaries used by ClimaTerm (GEMET, Reegle, DBpedia and ManualTerms) match terms within the tweet. To provide this heuristic ClimateTerm was extended to differentiate which terms were recognised by each specific dictionary. An example of the output provided by ClimaTerm can be seen in Figure 2. As we can see associated to each TweetID we have information about the climate terms identified by each of the four used dictionaries. In addition the annotation tools return a column indicating which of those terms are part of the hashtags of the tweet. Note that hashtags are used to reflect the main topics of the tweets, therefore tweets containing environmental terms as part of the hashtags tend to be more relevant or close to the topic of interest.

In addition to the automatic identification of climate terms, sentiment and emotion features are extracted by using the opinion mining tools developed in WP2. These tools are reported in D2.3.1. In particular, we have adapted the core opinion mining tools to extract emotions in addition to opinions (positive/negative/neutral sentiments), in order to perform a more relevant kind of classification for this task. Every sentiment therefore also has an associated emotion.

Negative sentiments are categorised as one of:

- anger
- disgust
- fear

- sadness
- bad (a generic category for anything not captured elsewhere)
- swearing (this could represent pretty much any of the above categories, but is also quite a specific sentiment. Note that swearing can also be positive when used as an intensifier - in this case it is not listed here but falls under one of the positive emotions)

Positive sentiments are categorised as one of:

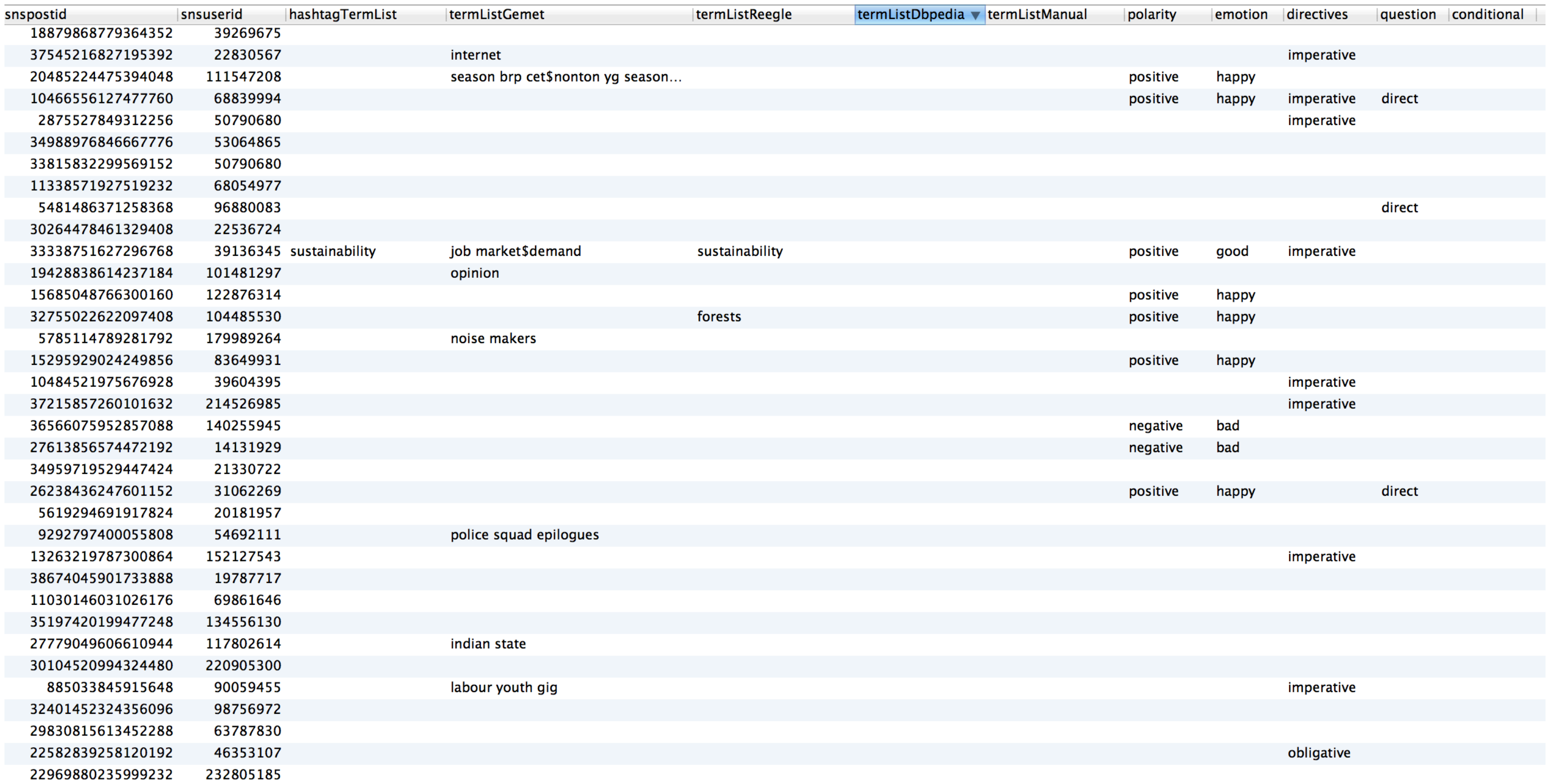
- joy
- surprise
- good
- happy
- cheeky
- cute

Finally, we have developed a tool specifically for this task, which categorises sentences according to a variety of linguistic modalities. The identified linguistic modalities include:

1. *Directives*
    - *obligative*, e.g. you must turn off the light
        - Note that a negative deliberative has an extra feature: “kind = negative”, e.g. “You must not turn off the light”.
    - *imperative*, e.g. turn off the light!
    - *prohibitive* (basically a negative imperative, e.g. do not turn off the light)
    - *jussive* (very rare - an imperative in the 1st or 3rd person, e.g. "Go me!")
    - *deliberative*, e.g. shall/should we turn off the light?
    - *indirectDeliberative*, e.g. "I wonder if we should turn off the light".
2. *Conditionals*, e.g. “if you don't turn off the light, you are a bad person”.
3. *Questions*

As specified in Section 3.3, linguistic modalities can be correlated with the behaviour cycle stages. For example, deliberatives are strongly associated with stage 1 (Desirable), while conditionals are (often) linked with stage 2 (Enable Context) and imperatives with stage 3 (can do). In addition to these

features we also consider the appearance of a URL within the tweet as an indication that the tweet contains relevant information about certain facts.



snspostid	snsuserid	hashtagTermList	termListGemet	termListReegle	termListDbpedia	termListManual	polarity	emotion	directives	question	conditional
18879868779364352	39269675										
37545216827195392	22830567		internet						imperative		
20485224475394048	111547208		season brp cet$nonton yg season…				positive	happy			
10466556127477760	68839994						positive	happy	imperative	direct	
2875527849312256	50790680								imperative		
34988976846667776	53064865										
33815832299569152	50790680										
11338571927519232	68054977										
5481486371258368	96880083									direct	
30264478461329408	22536724										
33338751627296768	39136345	sustainability	job market$demand	sustainability			positive	good	imperative		
19428838614237184	101481297		opinion								
15685048766300160	122876314						positive	happy			
32755022622097408	104485530			forests			positive	happy			
5785114789281792	179989264		noise makers								
15295929024249856	83649931						positive	happy			
10484521975676928	39604395								imperative		
37215857260101632	214526985								imperative		
36566075952857088	140255945						negative	bad			
27613856574472192	14131929						negative	bad			
34959719529447424	21330722										
26238436247601152	31062269						positive	happy		direct	
5619294691917824	20181957										
9292797400055808	54692111		police squad epilogues								
13263219787300864	152127543								imperative		
38674045901733888	19787717										
11030146031026176	69861646										
35197420199477248	134556130										
27779049606610944	117802614		indian state								
30104520994324480	220905300										
885033845915648	90059455		labour youth gig						imperative		
32401452324356096	98756972										
29830815613452288	63787830										
22582839258120192	46353107								obligative		
22969880235999232	232805185										

Figure 2: Screenshot of the Feature Engineering output

3.5. Semantic Modelling

We have adapted our initial semantic model (reported in D4.1) to include these features that characterise the users' behaviour, and in particular their behaviour towards the environment. Following the same approach as for modelling user preferences (extracted from the MESH ontology[5]), we extended our model to capture emotions, directives, etc. The performed extension is represented in Figure 3. As we can see, the class sioc:UserAccount is still the base class where information about the user is stored. To represent emotions we created two more classes: (i) the class UserEmotion, which represents the type of emotion that the user is expressing (anger, disgust, fear, joy, etc.), the time when the user expressed that emotion, and the post where that emotion was expressed; (ii) the class UserEmotions contains all the emotions that the user expressed over time. To model directives we followed the same approach as for modelling emotions: (i) we created the class UserDirective, which contains the type of language directive used (obligative, imperative, etc.), the time when that directive was used, and the post in which it was expressed; (ii) the class UserDirectives contains the series of directives used by the user over time within his/her posts. Note that in the model we only store the emotions and directives expressed by the users within those of their posts related to the environment (these posts were filtered by using the dictionaries and heuristics reported in the previous section)

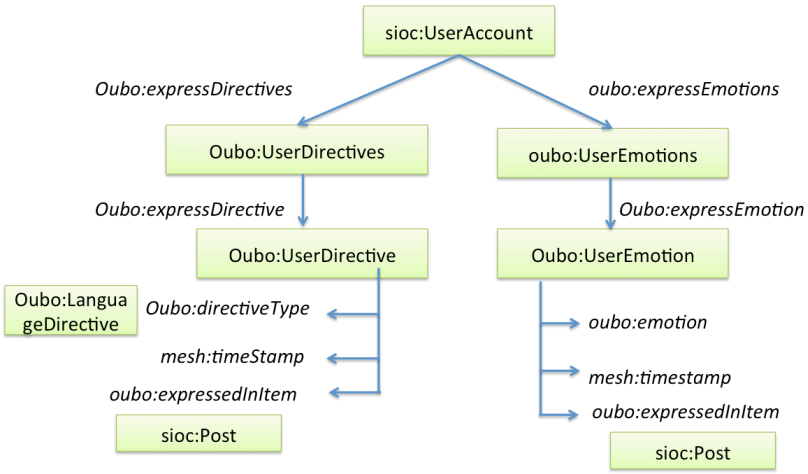


Figure 3: Extension of the OUBO ontology to capture the emotions and directives expressed by the user

[5] www.mesh-ip.eu/upload/MESH_user_ontology.zip

3.6. Behaviour Categorisation: A Supervised Approach

Once the new set of linguistic features was extracted and represented using our semantic model we have used these features to automatically identify behavioural stages. Our first approach has been to use the subset of annotated posts (see Section 3.2) to test multiple classifiers and to identify the most discriminative features to categorise posts within behavioural stages. In particular, Naïve Bayes, SVM, and decision trees have been tested using 10-fold cross validation based on the previously annotated dataset of tweets. The best performing classifier was the J48 decision tree (65.7% of accuracy).

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. As we can see in Figure 4 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 looks if the posts contains a URL.

Tweets 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 obligative or imperative the post is classified as stage 3 (can do), if there are non-directives in the text, the post is classified as buzz, and if there are other directives the classifier looks at the emotions in order to discriminate. If the sentiment is joy the post is categorised as stage 4 (invitation).

While this approach provides an easy and understandable set of rules to categorise posts into the 5 different stages of behaviour, the classifier was trained with a small subset of tweets (the ones manually annotated). Note that for creating supervised classifiers we need labelled data, which is very costly to obtain. Classification accuracy may therefore improve by providing the classifier with a larger dataset of annotated data.

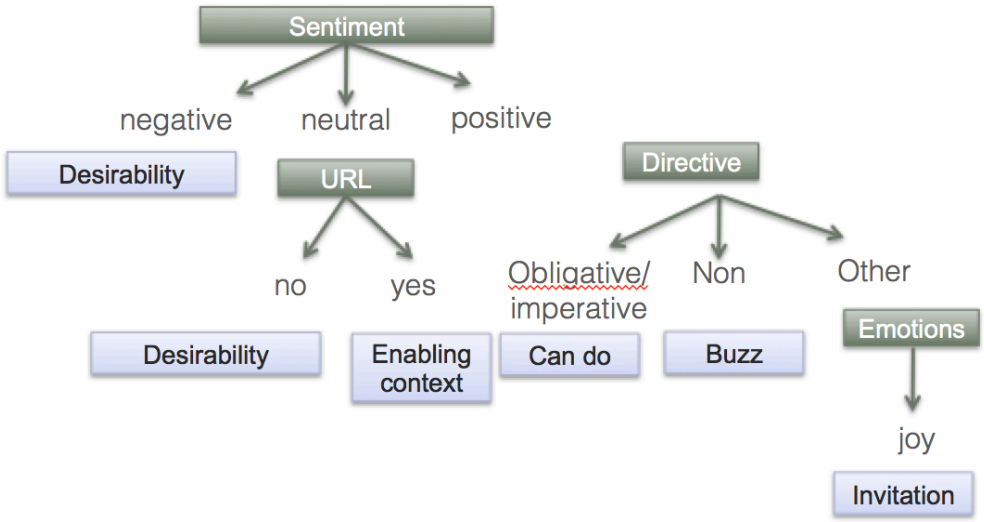


Figure 4: Rules for Behaviour Categorisation

We analyse the complete dataset of EH posts by using these rules. Our results show that, over the 56 million posts collected from the EH participants, 750,538 tweets (i.e., around 1%) are about the environment.

Within these tweets 66,576 (around 9%) have negative sentiment and are therefore classified as Desirability. Among the neutral posts 9089, (1.2%) do contain a URL, i.e., are classified as Enabling context and 443297 (59%) do not, i.e., are classified as desirability. Among the tweets with positive sentiment 82246 (around 11%) have obligative/imperative directives, i.e., are classified as can do, 145,585 (around 19%) do not contain any directive and are therefore classified as Buzz, and 3745 (less than 0.5%) are classified as invitation.

In summary, 68% of the environmental tweets are categorised in the desirability stage, 1.2% as enabling context, 11% as can do, 19% as Buzz and less than 0.5% as invitation.

3.7. Behaviour Categorisation: An Unsupervised Approach

Given the reduce subset of tweets from which our classifiers were trained and the cost of obtaining additional annotations, we experimented with an unsupervised approach to observe how posts were automatically grouped together based on the proposed features. Since the features/attributes that we are considering are categorical and not numerical, we couldn't make use of traditional clustering algorithms, such as K-means, without transforming the data.

Instead we made use of k-modes algorithm (Huang, 1997) an extension of the k-means algorithm. K-modes aims to partition the objects into k groups such that the distance from objects to the assigned cluster modes is minimized. By default simple-matching distance is used to determine the dissimilarity of two objects.

We applied k-modes to the subset of 750,538 tweets, i.e., those filtered as related to environmental issues by ClimaTerm. We use k=5 with the aim of observing how the data will group into 5 different subsets and if those subsets are actually representative of the behavioural stages identified by the 5-door theory.

The results of applying k-modes to these data show the following partition:

1. **positive happy imperative** nquestion nconditional
2. nsentiment nemotion **imperative** nquestion nconditional
3. **positive happy** ndirective nquestion nconditional
4. nsentiment nemotion ndirective nquestion nconditional
5. nsentiment nemotion ndirective nquestion **yes**

The first cluster is characterised for containing posts with positive happy sentiment and imperative directives (nquestions =no questions, nconditional = no conditionals). Examples of these posts are:

- “@Miss604 @VIAwesome @Treehugger help us share our #green #contest! We will be offsetting the winner's yearly driving emissions”.
- “It's #GlobalWindDay. Raising wind energy awareness to tackle climate change & give energy independence http://www.globalwindday.org/ @EWEA”

The second cluster is characterised by posts with neutral sentiment and imperative directives. Examples of these posts are:

- “The Future Sparks program will stage a zero carbon community concert on Sun 28-Nov. Learn how they'll achieve this: http://cross.lt/aec”
- “MON. APRIL 19 - 1st of three spring yard waste collection days. Follow these steps when putting your yard waste... http://bit.ly/bTwMla”

The third cluster is characterised for containing posts with positive happy sentiment and no directives, questions or conditionals. Examples of these posts are:

- “@windwatchorg great pt. of clarification! we're proud 2 work w/ @MonroeLitho 2 support #windpower growth w/ credits 4 their electricity use”

The fourth cluster is characterised by a neutral sentiment and lack of emotions, directives, questions and conditionals. Examples of such posts are:

- "My Zero Waste's Sunday roundup sums up a week of zero waste antics, including Cawleys Eco Eating! http://tinyurl.com/2vnuk42"

- "RT @WWF_Climate: #wwf Entertainment industry leaders premiere Earth Hour global music video on Facebook: http://bit.ly/c4wls6 #climate"

The last cluster is characterised by having conditional sentences and lack of sentiment and emotion.

- "RT @ViridorUK: Currently #energyfromwaste accounts for 1.5% in the UK but it could grow to 6% by 2015 if proposed infrastructure is perm ..."

- "RT @OntarioSEA: Hiring has only started, but if all the solar and wind production announced to date reaches its potential it could... ht ..."

As also revealed by the supervised approach, positive sentiment and imperative directives are discriminative of certain behaviours. However, after careful examination of the tweets grouped under each cluster, we believe that the provided partition of the data space does not correspond to the different stages of behaviour. This may indicate that either the selected features are not sufficient to group the data and discriminate the 5 different behavioural stages or that spurious data is differencing within the categorisation and needs to be filtered. As future work we aim to explore: (i) the incorporation of additional interaction features, traditionally used in the literature of social media analytics (see D4.1) as additional information to recognised behavioural stages, (ii) the use of filtering mechanisms to discriminate specific posts and users (such as agencies and other big media organisations) and (iii) the creation of a extended set of annotations from which more fine-grained characteristics of each behavioural stage can be learned.

4. User Behaviour within Climate Challenge

In addition to studying behaviour in social media, we have also analysed users' behaviour towards the environment by considering their participation in the Climate Challenge. The Climate Challenge is a game with a purpose, which provides an engaging way to help people learn more about Earth's climate, assess climate knowledge, and promote the adoption of sustainable lifestyle choices. The Climate Challenge was launched in March 2015 and offers 12 monthly game rounds per year where users accumulate points by solving game tasks, which can be related to:

- Awareness: Test your climate change knowledge

- Prediction: Correctly guess the future state of our planet, in terms of both global and regional indicators
- Change: Reduce your carbon footprint and adopt a more sustainable lifestyle
- Sentiment: Assess keywords in news media coverage about climate change

Users can guess answers, or take time to gather more information from a set of recommended links. They can only enter one guess per question (it cannot be changed after being submitted), and it must be entered before the stated deadline. To track results after having provided an answer, the system renders the diagram shown in Figure 5. It shows how the user's estimate compares to (i) the average of their own circle of friends, (ii) the crowd – i.e., all Climate Challenge participants, (iii) the experts' predictions, and (iv) the highest and lowest guesses. Once measurements are available, the diagram also shows how well the user did compared to (v) the actual real-world numbers, and lists the names of the top three users who had submitted the closest estimates.

To analyse behaviour in the context of the Climate Challenge we have studied the different features that can be extracted from the log analysis of this game and how these features can be used to recognise the different behavioural stages in which users are following the 5-door theory of behaviour change. The identification of the different behavioural stages in which users are can potentially enable a more targeted question/answering task in order to help users evolve faster in their cycle of behaviour change.

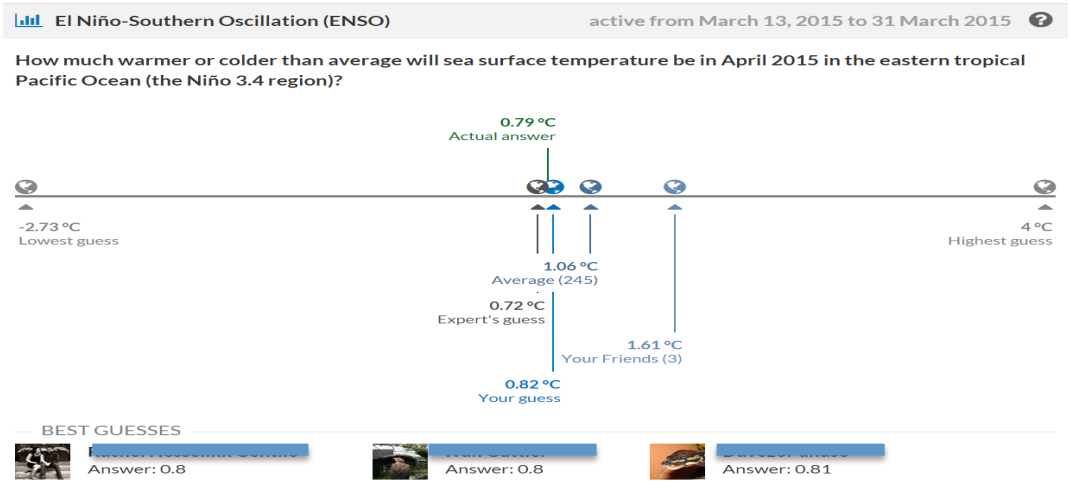


Figure 5: Comparative results of a prediction task, including a list of top-ranked players

4.1. Climate Challenge Data

We acquired log data for 442 participants of this game via WP3. This data contains information about the different times the users logged into the game, the answers they replied, the scores obtained when answering those questions, etc. In particular, these data is structured in the following tables:

- NOAA_WWF_questions: this table contains pledges proposed to the users (e.g., “Replace your bulbs and halogen spots as soon as possible with LED products, even when the old lights are still working. By doing this you help to protect the environment whilst saving money.”). Pledges are rated by users according to the impact they think the pledge will have.

- NOAA_WWF_answers: this table provides information of how users react to pledges (if they are already doing those actions, if they will consider doing them, and if not, what can be the reasons behind it)

- NOOA_sentiment_questions: sentiment questions are based on presenting the user keywords in news media coverage about climate change (e.g, carbon trading). The user then provides a judgement about the sentiment of that term. Different terms have different weights depending on the number of articles in which they appear. The higher the weight the more frequently the term will be presented to the user.

- NOAA_sentiment_answers: this table shows how different users rated the same keywords, in terms of sentiment, and when.

- NOAA_MC_questions: this table contains multiple-choice questions (e.g., “Are people driving their cars a cause of global warming?” yes/no).

- NOAA_MC_answers: provides the choices that users select for different questions and the time in which they reply to them.

- NOAA_guessing_questions: these are questions that the users guess about the future state of our planet (e.g., “Compared to the 20th century average, how much warmer or cooler will Earth's temperature be in May 2015?”)

- NOAA_guessing_readings: provides links with useful information that can help users to acquire knowledge to answer the guessing questions.

- NOAA_guessing_answers: this table contains the answers provided by the users regarding the guessing questions and when did they input those answers.

- NOAA_user_graph: This table contains the social media user profiles of those users that logged into the system using their Twitter, Facebook or Google+ credentials.

- NOAA_user_invites: This table contains which users have invited others to play the game.

- NOOA_user_bpoints: This table shows which userid has received bonus points (points) from another userid. This means the user has invited another user and now receives bonus points through his activities.

- NOAA_notification_points: This table contains the in-game notifications that the users have received. Users receive a message, every time they earn points, so they can look up their history in the notification area.

- NOAA_user_stats: contains statistics about the number of right and wrong answers input by each user.

4.2. Manual Inspection of Game Activities

Although both are social contexts, Twitter and the Climate Challenge provide different information about the users and their behaviour. While in Twitter users actively contribute by posting, as well as by retweeting, favouriting or replying to other users in the Climate Challenge interaction is based on participation within the questions as well as invitation to other participants.

Two different researchers carefully inspected the log data provided by this game in order to identify traces of behaviour that could help to automatically identify the different behavioural stages of the users.

The most important element identified during the inspection of the game's elements was pledges (NOAA_WWF_questions). Pledges define pro-environmental actions that the user can perform in their household/office/community. If a user is already doing the proposed action that means that the user is more likely to be in the stages of *buzz* or *invitation*. If the user accepts the action, that means the user is in the *can do* behavioural stage. If the user does not accept the pledge it means the user is still not conscious about the problem (i.e., they haven't started a cycle of

behaviour change) or, while they are aware of the problem (desirability) they haven't been able to enable context or take action yet.

The second element identified as very relevant to determine the users' behavioural stages is their participation and knowledge. We consider that the more a user participates and the more knowledge a user is acquiring, the more they are enabling context for a change.

The third key element that can be extracted from the game in order to determine the users' behavioural stages is invitation. It is important to remember that the users can invite other users to participate within the game. This generally corresponds to the later stage of a behavioural cycle, when users are already conscious and engaged with the environment and invite others to follow their steps and join their cause.

4.3. Feature Engineering

Based on the previous inspection of the game characteristics, we have come up with a set of features to automatically identify the behavioural stages based on the users' activities within the game. These features include:

- NPD: Number of pledges already being done by the user
- PAPR: Number of pledges rejected by the user
- NPA: Number of pledges accepted by the user
- NL: Number of times the user has logged into the game
- NRA: Number of right answers
- NUI: Number of invitations extended by the user
- SUP: Social user profile. This feature indicates if the users signed up with their Facebook, Twitter or G+ profile. In such cases users can interact with their friends within the game, which can also be considered a sign of invitation to participate

4.4. Behaviour Categorisation: An Unsupervised Approach

Considering that all the selected features are numeric we have performed a cluster analysis using K-means to determine how users group in different clusters according to the extracted features. We selected K=5 to observe how the clustering process maps with the analysis of behaviour. We normalise the attributes before performing the clustering process.

Attribute	Full Data (264)	0 (41)	1 (37)	2 (43)	3 (61)	4 (82)
doing	0.2867	0.2341	0.3865	0.2233	0.1672	0.3902
willdo	0.1473	0.1439	0.1676	0.0884	0.1918	0.1378
wontdo	0.1187	0.439	0	0.2016	0	0.0569
righta	0.3206	0.24	0.4912	0.2087	0.1028	0.5045
socialp	0.697	1	0	0	1	1
visits	3.3864	2.878	2.5946	2.5814	2.4098	5.1463

Figure 6: Cluster analysis for the participants of the Climate Challenge

As we can see from the above table, the larger cluster is number 4 with 82 users, while the smallest one is number 2 with 43 users.

Cluster 4 represents users that are already highly engaged with the environment (i.e., they are already participating in pledges) and are willing to take action and participate in more pledges. They have good knowledge about the environment and they participate in the game using their social media profiles (which is a sign of inviting others). Users under this cluster are therefore categorised as stage 5 (*invitation*)

Users in cluster 1 are also fairly engaged with pledges and also willing to take the challenge of new pledges. They also have a fair level of knowledge, although not as much as users in Cluster 4. These users, however, are still not inviting others to participate in the game. We consider users in cluster 1 in the Buzz behavioural stage.

Users in cluster 2 have the more diverse distribution between already participating in certain pledges, but not committed to participate in other ones. Their knowledge about the environment is also fair. We categorised this users under the "*can do*" behavioural stage.

Users in cluster 3 are still not actively participating into pledges but they are willing to do so. These users can be categorised under the "*enable context stage*".

Users in cluster 0 are not willing to participate in pledges (either because they can't or because they don't want to) but they have a decent level of knowledge about the environment. These users can be categorised under the *desirability stage,* they are aware of the problem but they haven't yet enabled the context to act on it.

5. Discussion and Conclusions

Engaging people with climate change by using technology as a medium not only requires the understanding of how technology can drive a behaviour change, but also the understanding of the needs and situations of the users in order to drive such a change.

In this deliverable we have presented the research of DecarboNet towards investigating the use of technology, and in particular social technology, to understand the behaviour of users towards the environment. In particular we have made use of Twitter, a microblogging platform, and the Climate Challenge, a game with a purpose developed within the context of DecarboNet.

We have proposed a general methodology to automatically identify the user's behavioural stages towards the environment based on the 5-door theory of behavioural change [Robinson, 2011]. Our methodology is based on three main steps: (i) a manual inspection of the data to identify the actions and interactions that can be gathered from the usage of the technology, (ii) a feature-engineering process, in which the actions, interactions and contributions of the users are transformed into numerical, categorical and semantic features, which can be automatically extracted and processed, and (iii) the application of supervised and unsupervised algorithms to mine patterns from the data based on those features.

The results of our analyses show important progress towards the identification of the different behavioural stages in which users are based on their generated content and interactions. In particular, sentiment, emotions and language directives have emerged as key linguistic features to identify behavioural stages in Twitter. In the context of the Climate Challenge, participation in pledges and acquired knowledge (based on the correctly answered questions) are seen as key features to identify behavioural stages.

This research is only an initial step within a complex research area and further investigations need to be conducted to understand the different factors that influence a behavioural change (i.e., an overtime progression/regression among behavioural stages). Understanding the factors that drive such change can help us to determine the optimal intervention strategies that should be applied at each stage of behaviour in order to successfully drive a change, or to stop the user regressing in his behaviour, therefore achieving a more stable and longer-term behaviour change.

A. List of Figures

B. List of Tables

C. List of Abbreviations

Abbreviation	Explanation
DM	Data Manager
WP	Work package
SW	Semantic Web
SIOC	Semantically Interlinked Online Communities
OPO	Online Presence Ontology
SemSNA	Semantic Social Networks Analysis
OUBO	Open University Behaviour Ontology
SWUM	Semantic Web User Model
PAO	Personality Assessment Ontology
SPIN	SPARQL Inferencing Notation
CQ	Competency question
UPO	User Profile Ontology

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