Paths to empathy: heterogeneous effects of reading personal stories online

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***Abstract*—Every day people share personal stories online, reaching millions of users around the world through blogs, social media and news websites. Why are some of these stories more attractive to readers than others? What features of these personal narratives make readers empathize with the storyteller? Do the readers' personal characteristics and experiences play a role in feeling connection to the story they read? Experimental studies in psychology show that there are several factors that increase empathy in the aggregate, but there is a need for deeper understanding of empathetic feelings at the individual level of storyteller, story, and reader. Here, we present the design and analysis of a survey that studied the impact of story features and reader predispositions and perceptions on the empathy they feel when reading online stories. We use causal trees to find the individual-level causal factors for empathy and to understand the heterogeneity in the treatment effects. One of our main findings is that empathy is contextual and, while reader personality plays a significant role in evoking empathy, the mood of the reader prior to reading the story and linguistic story features have an impact as well. The results of our analyses can be used to help people create content that others care about and to help them communicate more effectively.**

***Index Terms*—causal tree, empathy, online stories**

I. Introduction

Empathy is the ability to understand and share others emotions and is fundamental to connecting people in a community together [1]. Moreover, Mayshak et al. [2] showed that empathy increases user engagement in social networks, whereas Del Rey et al. [3] suggested that empathy decreases aggressive behavior, bullying and cyber-bullying. Experimental studies in psychology have discovered multiple factors that play a role in evoking empathy. For instance, when the emotions of a storyteller are intense and vivid, individual readers feel more empathy [4]. Another factor that plays a role is the relationship between the teller and readers; how similar readers believe they are to a storyteller has a strong impact on how much they will empathize with the storyteller [5]. Similarly, readers' characteristics, such as gender, age, and personality, influence vicarious emotions [6].

With the advent of social media, how we share and consume personal stories has changed significantly. In a matter of seconds, a story can reach and elicit reactions from millions of users. However, our understanding of the heterogeneity in people's reactions to online stories is lagging behind. Is there anything about your personal narrative that can make people empathize with you? What types of people would be more likely to connect to your story and share it with others? What is the role of mood in people's reactions and feelings of empathy? The answers to these questions are key to understanding how to create online stories that people can relate to and whether specific individuals will feel empathy for a given narrative.

To answer these questions, we collected and thoroughly analyzed data on people's reactions to written narratives of the best and worst events of individuals' lives. We recruited $2,586$ users on Mechanical Turk (MTurk) to read personal stories and rate how much empathy they feel for the storyteller. We then assigned them to multiple tasks to answer several questions such as rating different aspects of story and storytellers and describing how much similarity they felt with storyteller. We also collected information about the characteristics of the reader (demographic and personality), as well as asking participants to report their emotions before and after reading the story. In addition, from the narrative text we extracted LIWC features (Linguistic Inquiry and Word Count) [7] and moral foundations dictionary [8] to capture psychological aspects of each story.

Although several approaches have been developed in recent years to automatically detect empathy from text [9]–[11] using deep learning models such as Convolutional Neural Networks [12] and Long Short Term Memory networks [13], none of these approaches has focused on identifying the factors that explain the heterogeneity of empathy outcomes on people, which is our main research objective. Specifically, we focus on understanding whether the story features, reader predispositions, personality or demographic attributes contribute the most to how much empathy they feel. To this end, we propose to use trigger-based causal trees to discover heterogeneity of empathy using a number of possible treatments [14]. The goal of heterogeneous treatment effect estimation is to find subgroups of a population for which effects differ from the population as a whole. In particular, we study the effect of different attributes of readers' personality and demographic on how much the reader feels empathy for the storyteller after reading the story. For example, we may wish to discover how sub-populations differ in empathy based on the reader's personality traits.

This paper makes the following important contributions:

1) We provide a detailed analysis of how different story, personality and demographic factors can explain the

heterogeneity of empathy outcomes on people.

2) We show how the emotions of people can be effected by reading the different stories which can be useful in creating more customized online stories.

II. Related work

Decades of research in psychology and neuroscience suggest several factors that modulate empathy [15]–[18]. For instance, when a target's emotions are intense and described in vivid, realistic detail, individuals feel more empathy. In addition to these features of shared emotion, several works are done to show the relationship between the storyteller and the reader: what causes people to feel empathy for the storyteller when they read a story? For instance, Krebs [5] shows that when people believe they are more similar to a target (e.g., personality, values), they have stronger physiological responses such as increased heart rate and sweating to others pain. Likewise, how readers interpret a storytellers situation can amplify or extinguish empathy. In addition, when a storyteller is extremely sad about something the reader thinks is trivial (e.g., breaking up after two weeks of dating), the reader feels less empathetic sadness [19]. Moreover, the characteristics of the empathizer such as gender, personality, age, and past experiences influence vicarious emotions. When reading a story about someone losing their parent, individuals who had a similar experience were more moved by the story and felt more empathy [6].

Based on the above psychological and neuroscience aspect of empathy, there are several works that try to build empathy detection modeling using computational approaches with text and acoustic features. For instance, Gibson et al. [20] tried to find therapist empathy in clinical study interview sessions by using n-grams, POS tagging and psycholinguistic features. In another work, Alam et al. [21] annotated and modeled empathy in spoken conversations, based on multi-modal features extracted from conversations (such as acoustic features and video frames). Perez-Rosas et al. [22] studied linguistic and verbal behaviour (acoustic features) for predicting the empathetic behaviors of counselors during motivational interviewing [23]. More recently, several works explored deep learning models for detecting empathy from text [9], [11]. However, these models lack interpretability of results. Detecting causal relationships in data is an important data analytics task as causal relationships can provide better insights into data, as well as actionable knowledge for correct decision making.

Thus, the approach that we take is to identify causal factors that explain the heterogeneous effects of reading online stories, the relation between the reader and storyteller and the relation between the reader and various aspects of the narrative. There are several works that focus on developing more optimal precision treatment for diverse populations of interest, [24]–[27]. Heterogeneous treatment effect (HTE) estimation refers to finding subsets in a population of interest for which the causal effects are different from the effects of the population as a whole [28]. There are several techniques that have been developed for the problem of HTE estimation. Many works have focused on interpretable tree-based methods, such as decision lists [26] and decision trees [14], [25], [28]–[30]. Also, recently, random forest based methods have been developed for HTE estimation [31], [32]. These methods focus on cases when the treatment variable of interest is binary. In many real world scenarios, the treatment is an ordinal (or monotonously increasing continuous) variable, not a binary one, and the effect depends on the amount of treatment. For example, a psychologist might be interested to understand the amount of similarity between partners (the trigger) that any of those with unique personality need to have, in order to be connected (the effect). In [14], they focus on developing a learning procedure called trigger-based HTE estimation that enables the discovery of individual-level thresholds for triggering an effect. We consider the problem of trigger-based HTE estimation in our work, by finding triggers for variables of interest and finding heterogeneous subgroups where empathy is felt differently.

III. Empathy study

In this section, we describe the data we collected and the post-processing we applied to prepare it for analysis and causal modeling.

In previous work, we recorded over 700 videos in which 126 people described the three best and three worst events of their lives, and then we transcribed these 2-minute videos into text.Each script has binary sentiment labels if the event is positive and negative. In addition to these recorded videos, we also collected the information about the demographic (i.e., age, gender, race) and personality characteristics of each storyteller.

For our current study, we conducted a survey based on the transcribed stories and asked online participants to read these personal stories and then answer a number of questions using Amazon Mechanical Turk. We selected our target population from people who went to high school in US. The number of participants is $2,586$ and the number of stories used in the survey is 756. Each participant read one story, therefore each script is annotated by three people on average.

During the survey, we collected information about the characteristics of the reader (i.e., age, gender, race, personality) as well as their mood before and after reading the story. We also asked them to rate how much empathy they feel for the storyteller on a scale from 1 (A little) to 5 (Extremely). In the next step we asked participants to rate different aspects of the storytellers emotions (e.g., valence, intensity, and vividness). To understand their relationship with the storyteller, we also asked them to assess how similar they thought they were to the storyteller. Lastly, they evaluated various dimensions of the storytellers situation, such as how much they think the situation is out of the storytellers control, how responsible the storyteller is for the situation, and how extraordinary/unusual the situation seems. Together, these ratings allow us to quantify the psychological features that explain the levels of empathy for the storyteller.

A partial script given in the survey is shown in Table with some details changed to preserve anonymity I.

TABLE I: The example of partial script given in survey

So, for video number 4, Im going to be talking about the first negative event that I wrote down. That when I was bullied in the seventh grade. There was girl, and her name was Carol. She didn't like me. I don't know why. She just didn't. Then, she ended up turning the whole class against me. Nobody talked to me. I wouldn't even want to go to school. I would wake up and be like I don't feel good, I don't want to go. ....

In order to assess the level of readers' empathy with story tellers, we asked the following questions with answers on a scale from 1 (Not at all) to 5 (Extremely).

1) Please indicate to what extent you felt empathy for the storyteller.
2) Please indicate to what extent you felt each of the following emotions while reading the story.
   a) Sympathetic
   b) Compassionate
   c) Moved
   d) Envious
   e) Insecure
   f) Inferior

According to the psychology literature [33], there is always a large set of observed variables that correlate with each other and potentially a lower number of unobserved variables. Typically, factor analysis is applied to reduce the dimension of the dataset from many variables (observed) to few distinct new factors (unobserved). To measure Empathy, we used factor analysis which confirmed four variables as main empathy measure clusters in our sample, Empathy, Sympathetic, Compassionate and Moved with loading factors of 0.69, 0.80, 0.91, and 0.74, respectively. This measure of empathy is being used as the main output in all our analyses.

IV. Data

Next, we describe the data that we collected from the survey, together with the features we derived from the text.

A. Demographic and Personality features

We collected the demographic characteristics of each storyteller and MTurk participant, such as age, gender, race, and relationship status. In the MTurk population, 56% of the participants are female with average age of 38.6 (stdev 12.58). The average age of males is 36.56 (stdev 12.24). In terms of education level, 8% of the readers have graduated from high school and 53% from university. We discretized the income and defined 12 income scales from 1 (Less than \$10k) to 12 (more than \$150k). Over 54% of readers have income of less that $\$40k$ and less than 12% have income of more than $\$80k$. We asked MTurk participants to select all races they belong to, and 171 people declared more than one race. The highest race population is white and the second highest is black at almost 10% of the whole population which is almost following the same race distribution in US (White: 76.6%, Black: 13.4% source: US Census Bureau, 2018).

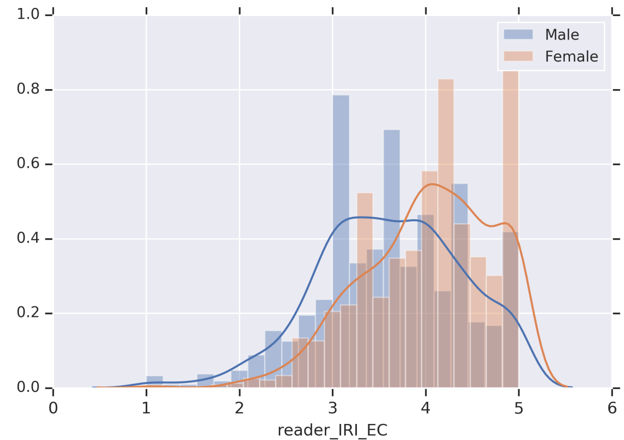


Fig. 1: Distribution of Empathic Concern (IRI_EC) across gender

We also collected the personality characteristics of each storyteller and MTurk participant including IRI (Interpersonal Reactivity Index), PE (Positive Empathy), Ten Item Personality Inventory, SWLS (Satisfaction With Life Scale) and loneliness (UCLA Loneliness SF). We used factor analysis, which is separate for storytellers and Mturkers, to categorize the personality traits into four main clusters: (i) Big Five Inventory (Extroversion, Agreeableness, Conscientiousness, Neuroticism, Openness), (ii) Loneliness, (iii) Positive empathy, and (iv) Interpersonal Reactivity Index for Perspective Taking (IRI_PT) and Empathic Concern (IRI_EC).

Table II shows the differences between personality traits across gender in our sample. In this table, IRI factors both empathic concern (IRI_EC) and perspective taking (IRI_PT) and together with positive empathy (PE), they all are significantly different across gender, with women being more empathic than men. Similarly, among Big Five Inventory personality factors, women show higher values of neuraticism and openness when compared to men. "Fig 1" shows the distribution of IRI_EC for both men and women which shows Women have higher (IRI_EC) comparing men.

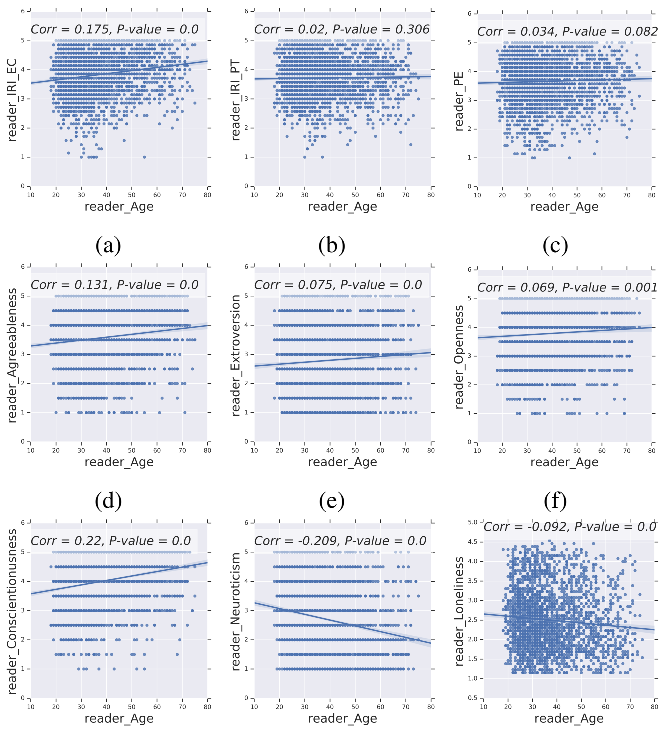
"Fig 2" shows how these personality traits differ by age. Agreeableness, Conscientiousness and Empathic Concern (IRI_EC) are positively correlated with age, while Neuroticism and Loneliness are lower for older people in our sample.

B. Emotions and mood

We collected the mood and emotions of readers before and after reading the story, in order to study how much participants' mood can affect whether they empathize with a storyteller and how much the story can affect their mood. The participants had to provide information on the extent (on a scale from 1 (Not at all) to 5 (Extremely)) to which they felt excited, pleased, afraid, and sad. The factor analysis suggests two main emotion clusters in our sample, positive and

TABLE II: Averages and t-test significance for personality traits and emotions of male and female readers.

	Female		Male			
	mean	std	mean	std	t_stat	p_value
IRI_EC	4.3	0.7	3.61	0.78	-14.127	0.0
IRI_PT	3.8	0.7	3.63	0.7	-5.83	0.0
PE	3.83	0.75	3.45	0.8	-12.59	0.0
Neuroticism	2.93	1.18	2.47	1.11	-10.01	0.0
Openness	3.83	0.93	3.7	0.9	-3.37	0.001
Conscientiousness	4.03	0.85	3.95	0.86	-2.3	0.022
Agreeableness	3.6	0.94	3.53	0.95	-1.8	0.073
Loneliness	2.4	0.77	2.5	0.78	0.52	0.60
Extroversion	2.77	1.11	2.8	1.08	.65	0.51



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 2: Changes in personality traits of readers across different ages.

negative. Table III lists the summary statistics for negative and positive emotions of readers before reading the stories. From this table, we can observe that on average, more people report on positive emotions than negative ones.

The survey is conducted on the best and worst events described by the storytellers which allows us to look at how positive and negative stories can shift peoples' mood. Table IV suggests that reading about negative events has the largest shift in positive emotion. At the same time, both positive and negative stories can shifting negative moods. Meanwhile, after reading positive stories, people's positive mood is not significantly changed on average (p_value = 0.227). "Fig 3' shows the distribution of moods before and after reading stories in more detail.

TABLE III: Basic summary statistics for Negative and Positive emotions of readers before reading the stories

	Negative emotion	Positive emotion
Min	0.76	0.78
Max	3.8	3.9
Mean	1.1	2.2
Std	0.53	0.77
Median	0.88	2.16

TABLE IV: Averages and t-test significance results for mood difference before and after reading the stories about positive and negative events

	Before		After			
	mean	std	mean	std	t_stat	p_value
PosEvent/PosEmo	2.2	0.76	2.16	0.85	1.2	0.227
NegEvent/PosEmo	2.2	0.77	1.3	0.57	32.059	0.0
PosEvent/NegEmo	1.1	0.52	0.93	0.42	8.999	0.0
NegEvent/NegEmo	1.1	0.53	1.3	0.53	-12.269	0.0

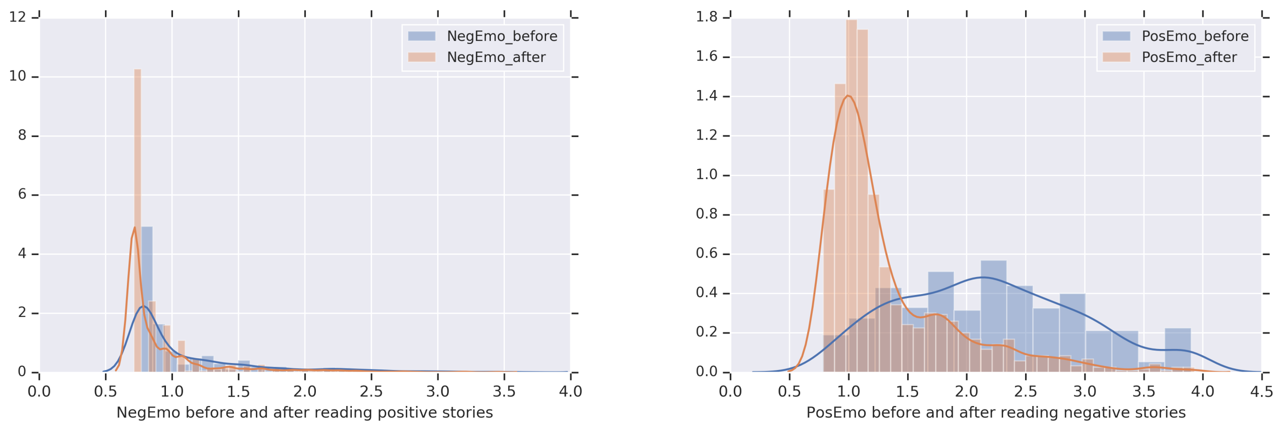
C. *Text features*

We are also interested in understanding what story features impact empathy and we derived psychological and moral features from each story. We used Linguistic Inquiry and Word Count, LIWC (http://www.liwc.net/) to determine the psychological dimensions of transcripts. LIWC is a text analysis program that counts words in psychologically meaningful categories. These categories include social, affective, cognitive, perceptual, biological processes, drives, time orientation, relativity and personal concerns [7]. Published papers show that LIWC have been validated to perform well in studies on variations in language use across different people [22].

Additionally, we use a dictionary from the moral foundations theory [8] which was developed to describe moral differences across cultures using five foundations with two extremes each: (1) care/harm, (2) fairness/cheating, (3) loyalty/betrayal, (4) authority/subversion, and (5) sanctity/degradation [34]. The dictionary identifies key words in the text that fall into 10 categories from the five moral foundations. For each story, we count the number of keyword occurrences that fall into the 10 categories. At the end, We normalize all the text features on a scale from 0 (A little) to 5 (Extremely).

V. HETEROGENEITY IN EMPATHY OUTCOMES

Heterogeneous treatment effect (HTE) estimation refers to finding subsets in a population of interest whose causal effects are different from the effects of the population as a whole. We treat all story features, storyteller attributes and reader characteristics before reading the stories as treatment variables to help us explain the differences in empathy outcomes. In this section we use causal trees to discover heterogeneity of empathy outcomes. First we give a brief introduction to heterogeneous causal inference, and how we map this problem for finding heterogeneous groups in empathy.



(a) Negative Emotion Positive Event

(b) Positive Emotion Negative Event

Fig. 3: Distribution of readers' emotions before and after reading a negative and positive stories.

A. *Heterogeneous Treatment Effects (HTE)*

The goal of our study is to find what attributes of the story, storyteller and reader play role in how much empathy participants feel after reading a story. Rather than looking for correlations between treatment variables and empathy, here, we take a causal approach where we looked for the differences in empathy outcome for readers that share the same characteristics but differ in treatment. Some of the treatment variables that we considered were based on the readers' personality characteristics, such as Extroversion and IRI_EC.

Formally, we frame our problem using the Neyman-Rubin framework of potential outcomes [35]. Let the treatment indicator for unit i be $t_i \in \{0, 1\}$, such that for a single unit i, there exists a pair of potential outcomes $Y_i(0)$ and $Y_i(1)$, the outcomes when non-treated and treated, respectively. For example, a unit in our study is a reader-story pair and a treatment can be whether a story is emotional or not. We can only observe the outcome from one of the treatments but not the other at any given point in time, e.g., how a person reacted when they read an emotional story, defined as $y_i = Y_i(t_i)$. Each unit is associated with a feature vector $\mathbf{x}$. Our dataset then consists of the triples: $\mathcal{D} = \{\mathbf{x}_i, y_i, t_i\}_{i=1}^N$. The goal of HTE estimation is to estimate the conditional average treatment effect (CATE) function, defined as:

$$\tau(\mathbf{x_i}) = \mathbb{E}\left[Y_i(1) - Y_i(0)|\mathbf{x_i}\right]. \tag{1}$$

When the treatment is a continuous or discrete variable, e.g., how emotional a story is, rather than a binary indicator, we define $t_i \in \mathbb{R}$ to be the amount of treatment for each unit i. We define a trigger as θ_i, which is the threshold for triggering a maximum effect. Then our pair of potential outcomes maps to the new trigger-based problem as: $Y_i(t_i \leq \theta_i)$ and $Y_i(t_i > \theta_i)$, which are the potential outcomes below and above the trigger, respectively. Then the goal is to maximize the trigger θ_i, in order to trigger the maximum causal effect:

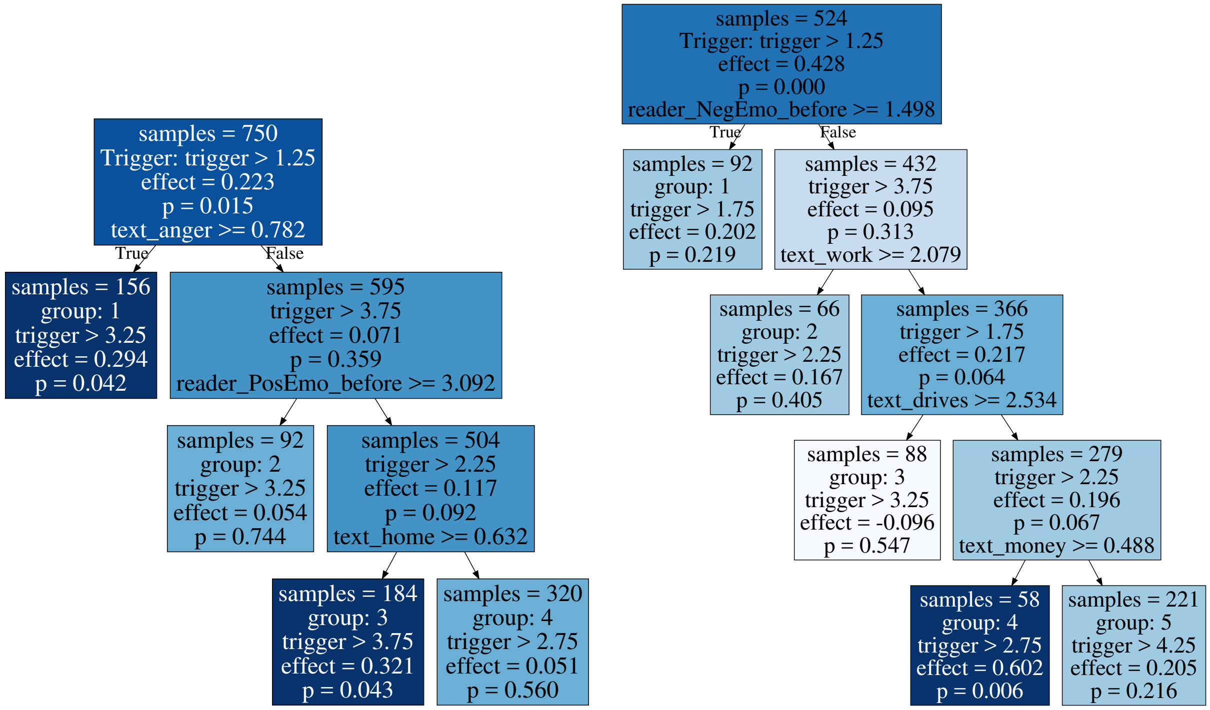
$$\arg\max_{\theta_\ell}\ \tau(\mathbf{x_i}) = \mathbb{E}\left[Y_i(t_i > \theta) - Y_i(t_i \leq \theta)|\mathbf{x_i}\right], \tag{2}$$

B. *Causal Trees for HTEs*

Recently, tree-based methods have become popular for estimating the CATE function [14], [28], [30], [36]. Causal trees seek to discover heterogeneity in causal effects, by maximizing the difference in estimated effects and finding feature splits via greedy criteria, similar to a decision tree. After a tree is built, paths to leaves estimate the CATE function $\tau(\mathbf{x})$, where $\mathbf{x}$ is a feature path to a leaf.

To build causal trees for estimating treatment effects on empathy, we leverage work from [14], [28]. Causal trees are built by greedily optimizing a mean squared error problem derived in [28], for finding the most heterogeneous subgroups at each split of the tree. In our work, we use a recently developed causal tree method that finds triggers when treatment values are not binary [14]. “Fig. 4” shows two examples of causal trees built from our data, one for the positive and one for the negative stories. At each level, of the tree, we estimate the CATE (effect) defined in (1) and (2) for the trigger case. For non-binary treatments, we also find the trigger that produces the maximum effect (biggest change in empathy).

”Fig 4.a”, shows an example of a causal tree built from the algorithm developed in [14] where the extroversion of the reader is considered as treatment. In each node, we have a trigger and an associated effect. The trigger is the threshold that maximizes the effect for the sub-population that is described by the path from the root to the current node. The trigger separates the population into two groups, those with treatment above the trigger, and those with treatment below the trigger. At each node, we test for a split that maximizes the difference in effect of child nodes. The trees are built recursively until the stopping criteria are met, as defined in [14]. We describe the specific setup and findings based on the trees in the next two sections.



(a) Negative stories (b) Positive stories

Fig. 4: Comparison between trigger-based causal trees (CT-H) for a) negative stories, and b) positive stories with treatment of reader extroversion (darker and lighter shading indicates treatment effect is higher and lower, respectively).

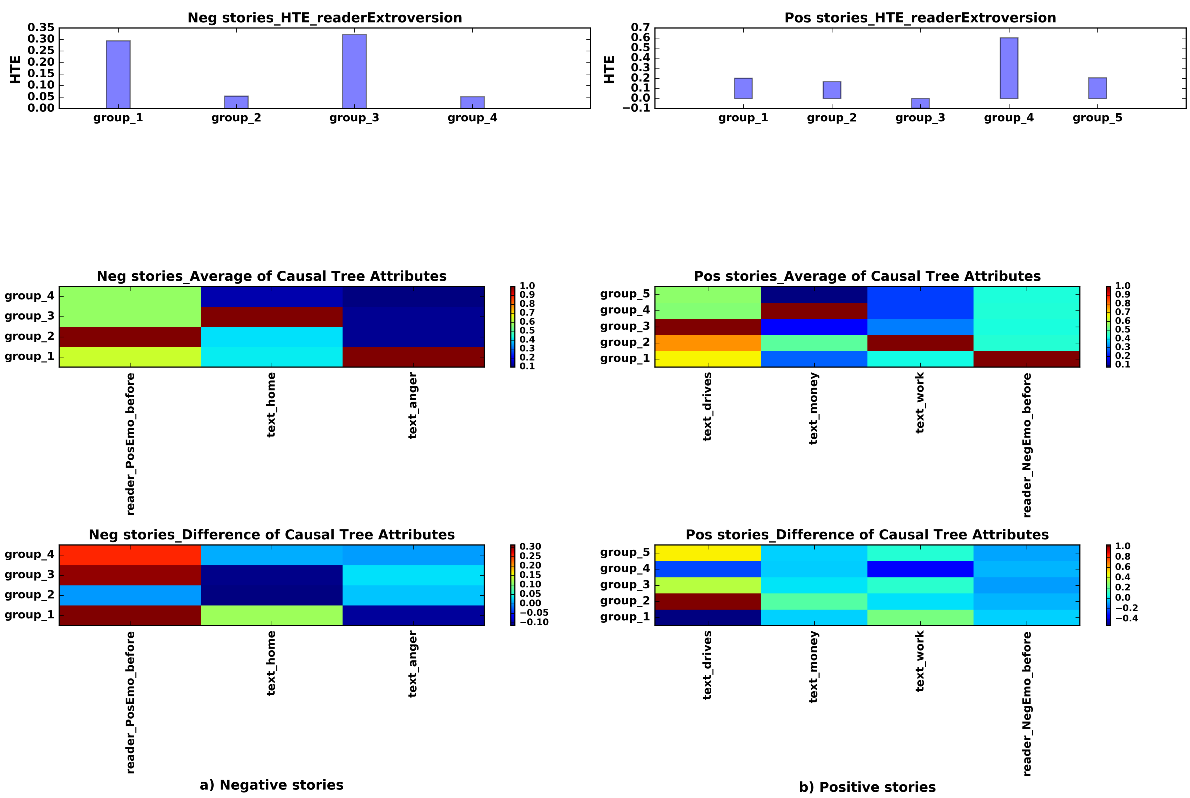


Fig. 5: Causal effects and attributes heatmap of readers' extroversion for negative and positive stories

C. HTE for Empathy

Studying empathy through HTE estimation would allow us to discover the different paths to empathy for people. For example, in one sub-population, having high positive emotion (before reading the story) could have a strong positive effect on feeling empathy, as compared to people who have low positive emotion. In other sub-populations, having a high positive emotion could have a more subtle effect due to other factors.

As discussed, six stories were transcribed for each storyteller as the best and worst events in their lives. We analyze negative and positive stories separately from each other. We considered four different treatment variables, both binary and discrete:

- readers' gender: binary indicator (0,1) whether the reader is male or female.
- readers' age: continues indicator of what is the readers' age.
- readers' extroversion: discrete scale (1-5) of how extroverted a reader is, where higher is more extroverted.
- readers' IRI_EC: discrete scale (1-5) of the reader's empathic concern.

In the case of non-binary treatments, we used trigger-based causal trees. For example, we investigated triggers (or thresholds) of how extroverted readers are, in order to find the highest possible difference in empathy. For example, the trigger for a subgroup could be low (e.g. 2), which means they would not need to be so extroverted to feel empathy, while others may need to be more extroverted (e.g. 4).

D. Discovering Causal Factors for Empathy

For the causal trees, the effect is the difference in empathy between a treated population and an untreated population, such that both have the same characteristics as defined by the causal tree path. When the treatments are non-binary, the trigger is the treatment threshold that resulted in the highest effect.

1) Readers' Extroversion: "Fig. 4" shows two causal trees built on the treatment of readers' extroversion for negative and positive stories. The trigger in this case is the minimum amount of extroversion that triggers the most empathy change. For example, in the root node of "Fig. 4.a", the trigger is 1.25 (1-5 scale of extroversion, where 5 is the most extroverted), which means that compared to extremely introverted users, everyone else (users with extroversion score greater than 1.25) is more likely (p_value=0.015) to feel more empathy.

Extroversion is a personality trait that has been linked to social engagement, so would plausibly dictate an individual's likelihood to engage with a story. But more specifically, extroverts' tendency to socially engage may be explained by an increase in reward sensitivity and a preference for positive emotion [37]. So we were interested to see if this would shake out of the analysis, and expected that extroversion might specifically drive engagement in positive stories, particularly when the narrative focused on rewarding topics.

First we will focus on positive stories. In line with literature, "Fig. 4.b", shows that conditioning on extroversion, readers will engage with positive narratives. This evidence is driven by how much the speaker discusses classically about rewarding topics like *text_drives* and *text_money*. These two text features split the population into two subgroups, where the empathy effects are different. *text_money* is a word category in LIWC which captures words like $audit$, $cash$, owe, and *text_drives* captures words like $motive$ and $power$.

These two text features, *text_money* and *text_drives*, suggest that extroverts are engaging based on the presence of rewarding topics. Although, according to our causal trees, different sub-populations are engaging with a heterogeneous subset of rewards. This is not particularly surprising, as it is well-understood that reward processes are domain-specific [37]. We all have vices, but we have particular vices (e.g., one person may engage when they hear about food, whereas another may engage when they hear about money). Individuals who are more reward sensitive are more likely to engage with rewarding content, but only if it is personally rewarding for them.

Another feature that plays a significant role in engaging readers with positive stories is their negative emotions before reading the story. Having negative emotions will result in more engagement with positive stories as those stores will shift readers' negative emotions.

In "Fig. 4.a", the root node splits into two children based on the feature *text_anger* (LIWC feature), and the effects in the two subgroups are different. This means that out of all the features, high extrovert people are empathizing with negative stories when the text includes *text_anger*. text_anger in LIWC captures words like $hate$, $kill$, and $annoyed$ [7].

In general, from "Fig. 4", reader's positive and negative emotions before reading the story play a significant role in how much empathy they feel, as these features appear in both negative and positive stories. The mean value of positive and negative emotions before reading the stories in IV, is evidence that shows how high arousal in emotions is effecting on more empathy. High positive emotions (reader_PosEmo_before >3.092) appear in negative stories, while high negative emotions (reader_NegEmo_before>1.498) appear in positive stories. Interestingly, the text features from LIWC are other important factors for heterogeneous effects in feeling empathy as well. "Fig. 4.a", shows that text_anger and text_home are affecting the way readers are empathizing with storytellers. Similarly, in positive stories "Fig. 4.b, text_money and text_drives are important for feeling different degrees of empathy.

"Fig. 5" shows more detail about each discovered HTE group, as identified by the tree leaves. The first two graphs show the causal effects for each of the four groups in the negative stories, and each of the five groups in the positive stories. The first two heatmaps show the average attribute values per group for all attributes that played role in building the tree. For example, in negative stories, high values of text_anger (including such words as $hate$, $kill$, $annoyed$), positive emotion before reading the text, and text_home (including such words as $family$) [7] explain how much readers feel empathy in group one, group two, and group three, respectively. In positive stories, "Fig. 5.b", group 4 has the highest effect and the text_money (including such words as $audit$, $cash$, owe) is the attribute that has the highest value on average within that group which show how much extrovert people are engaging with rewarding topics . The last two graphs show the difference in average attribute values between the treated and untreated in each group. For example, in group 1, there is a large difference in feeling positive emotion before between treated and untreated.

In general, we see that extroversion increases engagement with positive stories if they contain a lot of positive emotion and/or reward content; although, there are separable sub-populations that respond to different types of rewarding content.

2) Readers' Empathic concern: We also looked into the impact of personality and empathic concern (IRI_EC) on feeling empathy. Empathic concern is related to sensitive feelings toward those in needs and associated pro social behavior. As such, it was predicted that a readers empathic concern might be particularly relevant for driving engagement with negative stories. And we were particularly interested to see if any sub-populations emerge based on characteristics of the narrative.

"Fig. 6" shows causal trees built on the treatment of readers' IRI_EC for negative and positive stories. Minimum amount of IRI_EC is the trigger in these trees in order to find the highest empathy change. Triggers' values and p_values in both negative and positive stories show that this treatment has a significant role in feeling empathy,as expected. From "Fig. 6", in contrast to Extroversion, only positive emotion of readers before reading the story has an effect on how people feel empathy. For people with high empathic concern, positive emotions are playing an important role to empathize with storytellers.

Another interesting aspect of the discovered groups is that the LIWC text features that explain the effect heterogeneity are different for Extroversion and IRI_EC. "Fig. 6".a shows that $risk$ words (mean = 0.48, std = 0.7) and pos_emo words (mean = 1.37, std = 0.83) play a role when reading negative stories. For positive stories, $work$ words (mean = 0.8, std = 0.8), $home$ words (mean = 0.56, std = 0.73) and neg_emo words (mean = 1.00, std = 0.88) explain groups with different levels of empathy. An interesting point here is that positive words in negative stories and negative words in positive stories are playing a big role in feeling empathy differently. For example, from "Fig. 6".a, we can observe in order to empathize with negative stories, you need to be more positive (reader_PosEmo_before ≥ 2.924). In addition you need to see more positive words (text_posemo ≥ 1.458). This observation shows how people can empathize more with negative stories when there is still some positiveness in the story and vice versa. Another interesting point from "Fig. 6" is that the level of perspective taking ability (IRI_PT) of the storyteller impacts the readers' empathy in positive stories.

3) Readers' Age and Gender: Causal trees with gender and age of readers as treatment showed no significant effect on causing people to feel different levels of empathy except for few groups. From Table VI, we can observe that older people are empathizing with storytellers more than younger ones, but there are different sub-populations so it is not an across the board effect. In some cases, the effect is negative. This means that in certain subgroups, older people are *less* likely to feel empathy than younger readers. For example, in Table VI, under Negative Stories, group 5 and group 7 have negative effects, where older readers feel less empathy than younger readers.

TABLE V: The causal effect of readers' gender (female as treatment) on empathy for discovered HTE groups in negative and positive stories

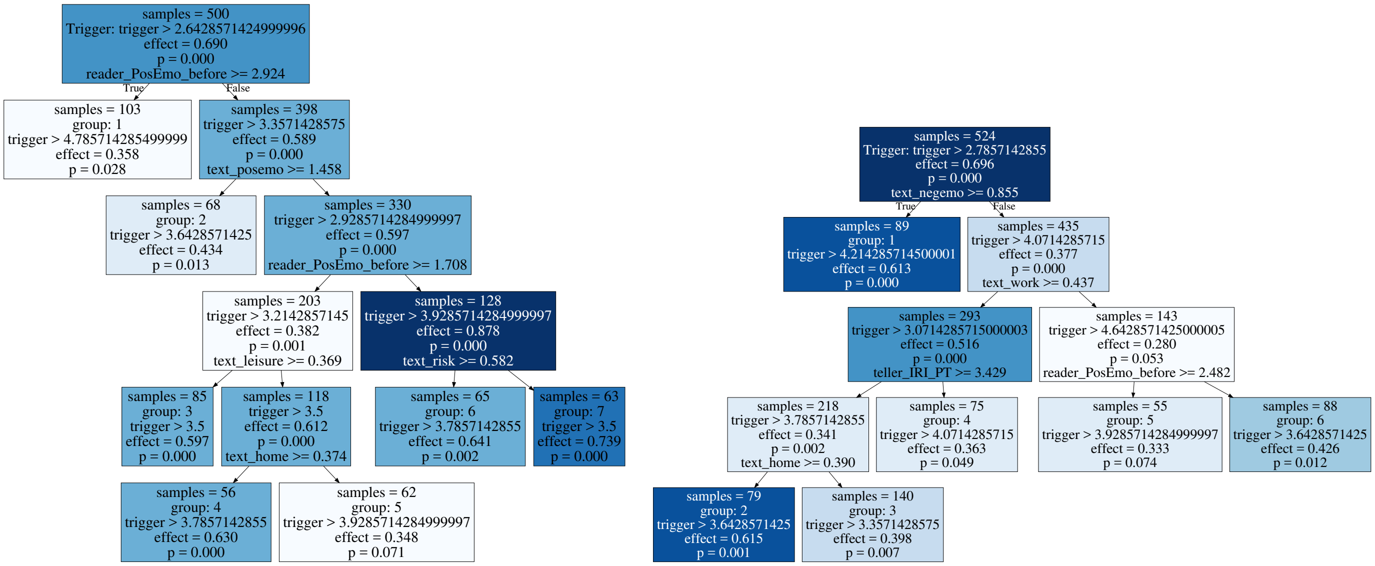
	Negative Stories		Positive Stories	
	effect	p_value	effect	p_value
group 1	-0.051	0.911	-0.107	0.726
group 2	-0.678	0.068	-0.148	0.539
group 3	-0.085	0.845	-0.015	0.971
group 4	0.597	0.031	-0.212	0.497
group 5	0.291	0.472	-0.015	0.961
group 6	-0.561	0.108	-0.042	0.888
group 7	0.325	0.450	-0.432	0.368
group 8	-0.039	0.925	0.003	0.992
group 9	-0.033	0.905	0.026	0.917
group 10	0.053	0.799	0.144	0.758
group 11	-0.345	0.328	-0.463	0.019
group 12	0.546	0.045		
group 13	0.298	0.211		
group 14	0.691	0.013		
group 15	-0.019	0.945		

TABLE VI: The causal effect of readers' age on empathy for discovered HTE groups in negative and positive stories

	Negative Stories			Positive Stories		
	effect	p_value	trigger	effect	p_value	trigger
group 1	0.16	0.244	39	0.019	0.918	29.5
group 2	0.123	0.456	43.5	-0.081	0.644	33.5
group 3	0.3	0.092	39.5	-0.112	0.410	39.5
group 4	0.314	0.114	40.5	0.009	0.958	41.5
group 5	-0.072	0.724	36.5	0.279	0.09	36.5
group 6	0.118	0.554	34.5	0.386	0.024	31.5
group 7	-0.072	0.043	34.5	0.199	0.174	32.5

VI. Conclusion

In this paper, we explore the question of whether some personal stories online, are attracting more readers than others and whether either story features or readers' personality characteristics are playing an important role in readers empathy with storytellers. Using the data collected by our designed survey, we showed how story features and reader characteristics (personality and demographic) can affect the empathy they feel when reading online stories. We used causal trees to understand the heterogeneity of empathy outcomes when reading the online stories. Our experiments show how some of personality characteristics of readers are effecting the empathy that readers feel. While age and gender as treatment did not help us discover significantly different groups, personality



(a) Negative stories (b) Positive stories

Fig. 6: Comparison between trigger-based causal trees (CT-H) for a) negative stories, and b) positive stories with treatment of reader empathic concern (IRI_EC) (darker and lighter shading indicates treatment effect is higher and lower, respectively).

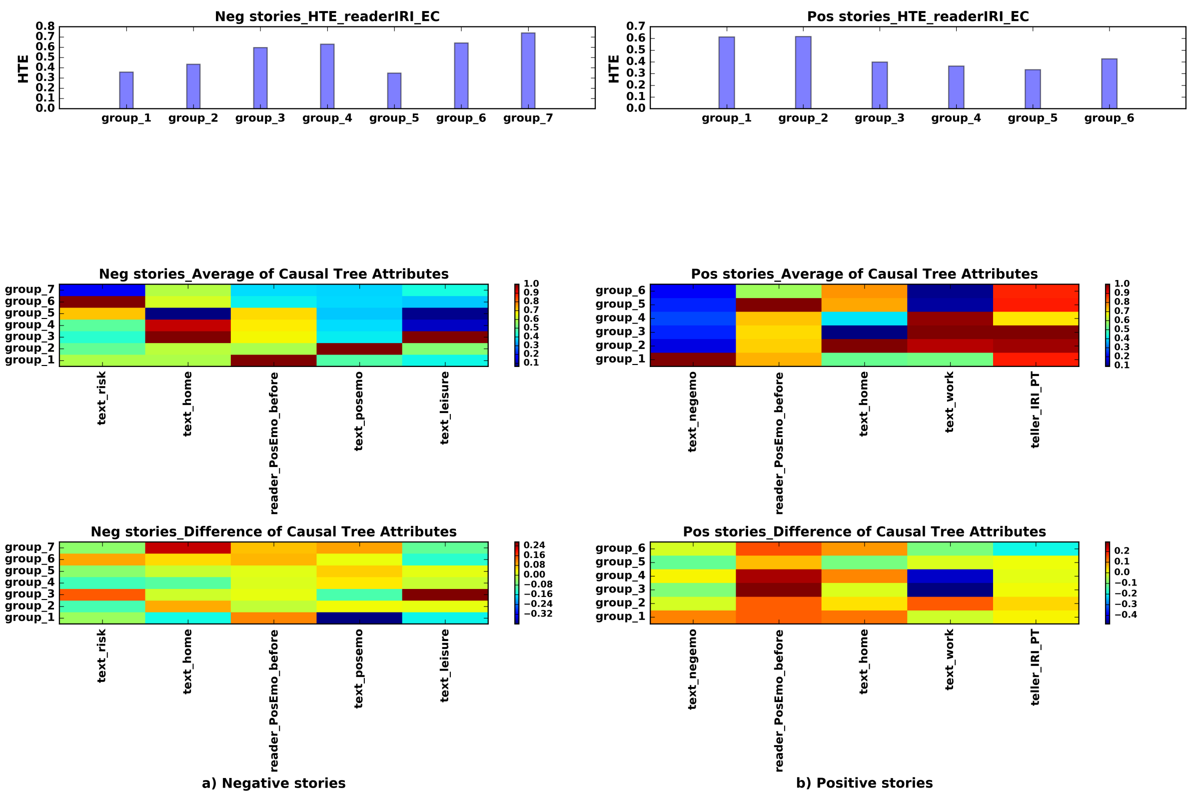


Fig. 7: Causal effects and attributes heatmap of readers' IRI_EC for negative and positive stories

characteristics like extroversion and empathic concern did. One of our findings was that the linguistic features of the story and reader mood before reading the story have a significant role in the paths to empathy.

There are a number of future directions we plan to pursue. First, we are interested to explore how other attributes of stories, such as logical, vivid, and social, are effecting the feeling of empathy. We also plan to incorporate external factors such as text features (e.g., size, font, color) and images in order to understand how people react to those stories and finally help people create content that is better tailored to their audiences.

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