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An Environment for Transforming Game Character Animations Based on Nationality and Profession Personality Stereotypes

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Abstract

A vast body of literature has dealt with the challenges of creating the impression of human appearance and human-like motion in the animation of game characters. In this paper, we further refine these efforts by creating a flexible environment for animating game characters endowed with personality, which is a core descriptor of stable characteristics of human behavior and which is often expressed in human movement. We base our work on the Big Five personality traits, also known as OCEAN (Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism). Our environment incorporates a procedural mapping from OCEAN personality traits to movement modifiers that alter existing motions in ways compatible with a desired personality.

Using Amazon Mechanical Turk, we collected stereotypical personality profiles for 135 nationalities and 100 professions. We integrated these stereotypical personality expectations into an interactive interface in Unity3D. Users can linearly blend the nationality and profession OCEAN parameters and individually adjust them for specific characters or groups. The results are validated using Amazon Mechanical Turk pairwise judgments on character types based on movements.

Introduction

Human-like motion is of critical visual importance in many game genres, and is usually created with motion capture or manual animation. These methods impose a rigidity on the game design as characters move only as conceived. In other aspects of game design, procedural animation techniques are profitably employed to generate landscapes, buildings, and even game levels. But procedural alterations to human character motions may be limited to inverse kinematics for reaching or holding objects, or locomotion adaptations to terrain variation, navigable regions, or user speed and directional controls.

From human experience we also intuitively recognize that personality may affect movement. There is now a considerable literature in the embodied virtual agent community on how personality models influence motion in all body systems, including body posture, gait, arm gestures, and faces (Gratch et al. 2002). Recently we have developed a procedural mapping from OCEAN personality traits (Openness, Conscientiousness, Extroversion, Agreeableness, Neuroticism) (Goldberg 1990) to movement modifiers so that any input motion can be adapted to any input OCEAN values [under review]. We will summarize this mapping and how we obtained it in the Personality to Movement Mapping Section.

Setting suitable OCEAN values for a particular character (or group of characters) becomes a potential problem. While a game designer could guess at suitable OCEAN values, providing some initial guidance on possible meaningful or stereotypical values could be of great value. Our system allows the rapid transformation of existing animated character motions to new stereotypical nationality or profession targets without recapturing or manually altering existing character movements. Modeling a viewer's expectations about the personality of commonly encountered groups, such as characters with a given profession or nationality, allows us to provide developers with reasonable starting points for animation of a large set of possible game settings. Rather than thinking about suitable parameters for each individual character, developers can draw on general characteristics of the characters, e.g. a general expectation of how a German professor behaves. The developers can use the stereotype, deliberately manipulate the stereotype to create a desired effect on the perception of the player (for example by creating characters that challenge the stereotype) or exaggerate a stereotype to the point of a caricature which may help players reconsider their own bias.

In this paper, we first summarize related work in agent personality modeling. Then we describe the methodology for and results of building a mapping from OCEAN personality traits to movement parameters. Then we detail the Amazon Mechanical Turk (AMT) studies we conducted to assess stereotypical OCEAN personality traits from 135 nationality groups and 100 professions, and summarize the results. We then illustrate the usage of this data through an interactive interface in Unity3D to assign individuals or groups a nationality and profession. We describe an AMT experiment to help validate the effectiveness of portraying nationality and profession in a character. The paper concludes with observations, implications, and possible future applications.

Related Work

OCEAN: The five-factor model of personality

Psychologists have been concerned for a long time with the question of how to effectively describe human personality. The five-factor model has emerged as the dominant view that best captures the variability in personality traits exhibited by people (Wiggins 1996). The underlying idea is that human language contains all descriptors pertinent to the perception of personality. A large list of descriptions of people, such as *studious, timid, friendly* were presented to subjects, who had to mark which descriptors best describe them or people that they know. Factor analysis was performed to find the groups of descriptors that explain the largest variance in the collected personality descriptors. Then researchers inspected the words in each group. Across many studies and initial starting descriptors, five groups of descriptors emerged as explaining the most variance. Researchers inspected the descriptors in each group and gave more general names to each. The vast majority of studies identify Openness to experience, Conscientiousness, Extroversion, Agreeableness and Neurotisism (OCEAN) as the main personality factors. We make use of this established framework in our work.

Movement and Personality

How to convey personality through movement styles has been an interesting topic for virtual agent researchers. Animators exploit the relationship between subtle motion characteristics and their psychological basis to give visual insight into a character's unseen personality. For instance, Chittaro and Serra report that neuroticism influences speed of animations, while extroversion influences the interpersonal distance between characters (Chittaro and Serra 2004). Neff et al. evaluate the perception of extroversion and emotional stability based on gestures and certain motion parameters (Neff et al. 2010; 2011). They state that non-signaling hand gestures significantly increase the perception of neuroticism and report a positive correlation between gesture rate and performance with perceived extroversion. Durupinar et al. (2011) examine the link between all five factors of the OCEAN personality model and human steering behaviors in a crowd. Similar work by Guy et al. (2011) introduces a system that derives a mapping between simulation parameters related to steering and personality traits of individuals within a crowd.

Stereotypes and Personality

Cross-cultural studies on personality traits have been performed on self-assessment reports or intra-cultural observations (McCrae and Allik 2002; McCrae and Terracciano 2005; Schmitt et al.). Systematic comparisons have shown that national character stereotypes are not always accurate (McCrae et al. 2013; Terracciano et al. 2005). However, because our purpose is to create realistic moving virtual characters rather than to assess the actual characteristics of cultures or professions, we rely on stereotypical perceptions rather than the accurate characteristics of nations or professions.

Relationships between personality traits and occupational interests, academic major preferences and job success have been investigated in the literature (Barrick, Mount, and Gupta ; Pringle, DuBose, and Yankey 2010). However, a well-defined link between the five factors of personality and occupational stereotypes is yet to be explored.

Personality to Movement Mapping

We have defined a mapping between the characteristic parameters of human movement and different personality traits in order to synthesize motions with personality (Durupinar et al. 2016). To avoid arbitrary selection of motion parameters among a wide array of possible parameter choices, we have employed Laban Movement Analysis (LMA). LMA is a technique for systematically and qualitatively evaluating human motion. In our system, LMA acts as an "interlingua" to translate between low-level motion parameters and personality.

To obtain the mapping, we conducted a study with two certified LMA experts to select low-level parameters that effectively represent LMA elements and derive a mapping between these movement parameters and LMA qualities. Then we implemented and extended the EMOTE system (Expressive MOTionEngine), introduced by Chi et al. (2000) to implement low-level motion parameters. Finally, we performed a perceptual user study to derive a mapping between LMA parameters and the OCEAN personality model. We thus generalized the representation of personality across various motions and virtual characters.

As a result, we can effectively map personality factors to LMA settings, which are mapped in turn to movement parameters to generate personality-driven motion.

Nationality/Profession Stereotypes to Movement Mapping

We performed Amazon Mechanical Turk studies to identify likely stereotypes associated with personality and nationalities and professions, then used these stereotypes to modify virtual human character motions. Different cultures and professions can be used to design personalized non-player characters (NPC) in computer games. NPCs conforming to stereotypes can increase player satisfaction by enhancing believability and international game deployment. The stereotypes we collected were only used to modify body motions; we did not address or change complexion, clothing, facial appearance, or speech.

The study of stereotypes regarding people with particular nationalities (Katz and Braly 1933; Madon et al. 2001) and professions (Kaler, Levy, and Schall 1989; Hareli, David, and Hess 2013) is a delicate issue because the stereotypes could be perpetuated or misused to manipulate opinion. The situations under which stereotypes are triggered and applied have been studied extensively (Devine 1989; Bargh, Chen, and Burrows 1996). Stereotypes can lead people to unreasonable attitudes and conclusions (Tversky and Kahneman 1974). Our goal is to draw attention of researchers in digital entertainment and artificial intelligence to the existence of stereotypes. As the field matures, such knowledge can be used to create digital environments that help people become

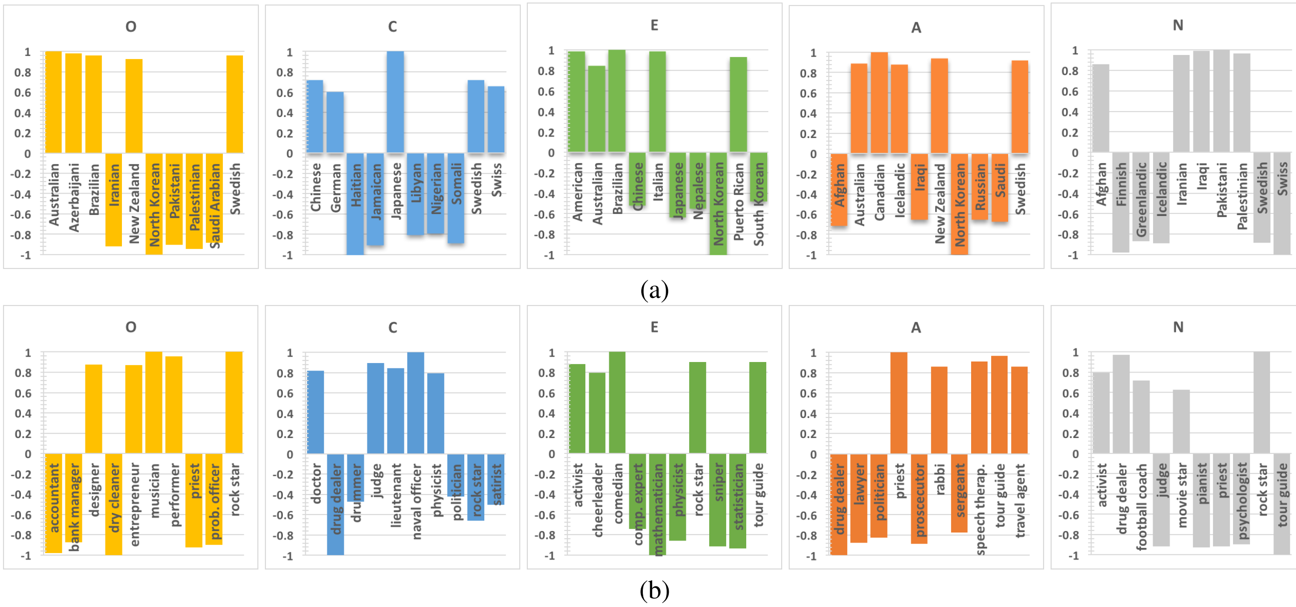


Figure 1: 10 (a) nationalities (b) professions with the most extreme O,C,E,A,N values

aware of their own stereotypes and possibly even overcome the stereotypes.

Ten Item Personality Inventory

There are several instruments for assessing personality traits (Costa and McCrae 1985; McCrae, Costa, and Martin 2005), all involving lexical descriptions of the two extremes for OCEAN dimensions. We used the compact Ten Item Personality Inventory (TIPI) (Gosling, Rentfrow, and Swann 2003), a validated tool for measuring OCEAN in subjects. TIPI, with its brevity and acceptable levels of convergence, is a suitable scale to use in large-scale, time-limited experiments. In TIPI, the OCEAN dimensions are defined on the following spectra, each exemplified by two lexical descriptions:

O: *conventional, un-creative* – open to new experiences, complex
C: *disorganized, careless* – dependable, self-disciplined
E: *reserved, quiet* – extroverted, enthusiastic
A: *critical, quarrelsome* – sympathetic, warm
N: *calm, emotionally stable* – anxious, easily upset

Nationalities and Professions

We collected human judgments about the stereotypical expectations related to personality for 135 nationalities and 100 professions. The list of nationalities was drawn from the CIA Factbook (Agency 2016) and pruned down to a smaller list of 135 common nationalities. Professions were drawn from WordNet (Fellbaum 1998). Specifically, the 100 professions were chosen among the children of the node "Person" in the WordNet *Is-a* hierarchy.

Stereotype Collection on Amazon Mechanical Turk

We recruited participants using Amazon Mechanical Turk to collect 30 judgments for the expected personality of each target nationality or profession. We restricted participation to United States-based workers in order to minimize culture-based biases. 363 unique AMT workers (161 males/202 females, ages 36.92 ± 12.55) participated in the stereotype collection experiment.

Each task addressed a single OCEAN personality trait, and consisted of 10 nationalities or professions. For each of these, subjects were asked to note on a 7-point Likert scale the degree to which they agree or disagree that a person with the given nationality or profession is likely to have the properties defining the ends of the TIPI scale. Zero is interpreted as having no expectation about the personality trait, -3 is interpreted as strong expectation that a person with this nationality will have personality as described by the descriptors of the negative end of the scale, 3 is strong expectation that a person from the target group will have characteristics associated with the descriptors of the positive end of the personality dimension. The order of target groups was randomized for each annotator. One target group was repeated for quality control. The judgments of the annotators were discarded if they gave different judgments for the repeated item. Judgments were also excluded if the annotator gave the same scores for each target group on the list. Also, in order to ensure quality, we required participation qualifications as having an acceptance rate of $> 95\%$, with an experience on more than 100 human intelligence tasks (HITs).

Analysis of Stereotype Data

We performed a Z-test to compare with zero the mean rating for each target group for the OCEAN dimensions. At the 95% confidence level, more than half of the professions and nationalities have average ratings that are statistically significantly different from zero (Appendix). This finding shows

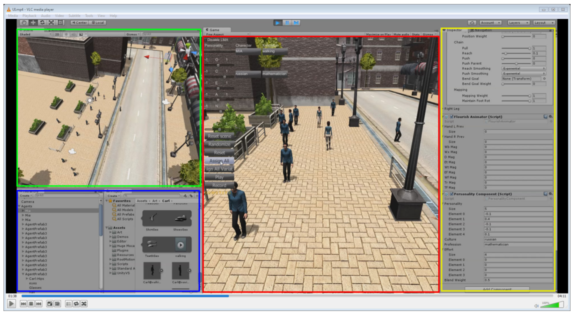


Figure 2: Interface layout: *Scene* window is highlighted by the green outline; assets can be selected from the elevated view camera of this window. *Hierarchy* window is highlighted by the blue outline; all names of the assets are listed in this window. *Game* window is highlighted by red outline; the global controller for OCEAN parameters and stereotypes are placed in this window. *Inspector* window is highlighted by the yellow outline; the control panel for an individual is placed in this window.

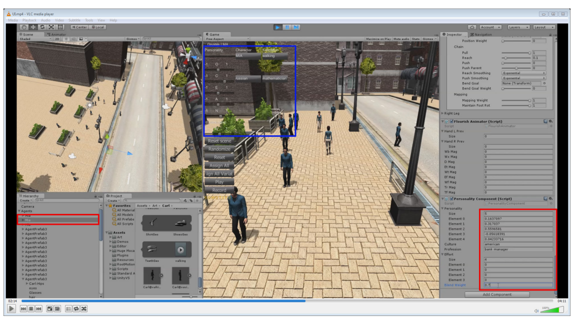


Figure 3: Parameter handlers highlighted in the blue outline show the current OCEAN values assigned to all agents in this scene. Individual agents can be further selected in *Hierarchy* window and tuned in *Inspector* window as displayed.

that people do have stereotypes about the expected personality of people from given nationalities and professions.

Fig. 1 shows the most extreme personality stereotype values for nationalities and professions. We computed the personality values by averaging the participants' answers for each nationality/profession and then mapping the values to $[-1, 1]$ for each personality trait.

The Interactive Environment

We built an interface for easy manipulation of personality driven motion synthesis for users who have no professional knowledge of OCEAN personality traits. The interface provides a list of professions and nationalities to the user. The OCEAN traits are automatically computed according to the user's selection of stereotypes. Personality values are computed by averaging the AMT participants' answers for each nationality/profession and then mapping the values from $[-3, 3]$ (the 7-point Likert scale) to $[-1, 1]$ for each personality trait.

Fig. 2 displays the interface we built in Unity3D. The control panel in *Game* window is the global modifier for adjusting the personality traits and selecting nationalities and professions; the control panel in *Inspector* window is the individual modifier. We also introduce a blending handler to mix the effects of both nationality and profession OCEAN values (which are probably different). The blending weight can be specified by the user. We use a linear blending model so that users can obtain the mixed results as:

$$P_{Final} = wP_{Nationality} + (1 - w)P_{Profession} \quad (1)$$

where P_{Final} is the displayed 5-dimensional vector of OCEAN personality traits, and $w \in [0, 1]$ is the blending weight.

Once the user completes the selection and adjustment in the global panel, the computed OCEAN values are assigned to all agents in the scene. For the case shown in Fig. 2, we assigned all agents to be "Russian Mathematician", therefore their personality traits are computed as $(-0.1, 0.4, -0.1, -0.1, 0.1)$ with a blending weight of 0.5.

After the global assignment process, adjustments on individual agents can be done by diving into their panels. For instance, Fig. 3 displays how we assigned one agent in the scene to be an "American bank manager" by selecting "American" and "bank manager" in the corresponding input boxes to alter the OCEAN values. The personality traits of this specific agent become $(0.16, 0.31, 0.56, -0.056, 0.042)$ with the blending weight $w = 0.7$.

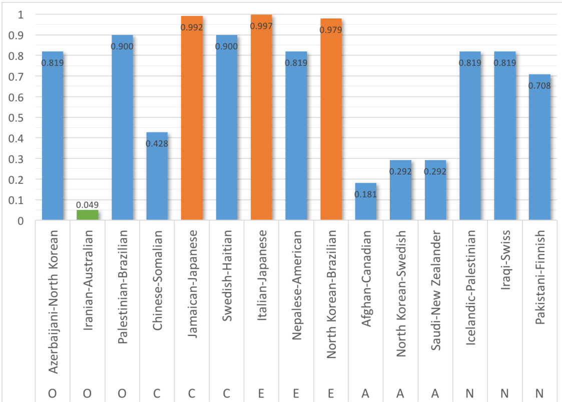
Evaluation

We evaluated how well people can recognize the stereotypes via the animations generated from our environment with another Amazon Mechanical Turk study. 113 unique workers (64 Male, 49 Female, age 33.34 ± 8.83) participated in the experiments. We collected 30 judgments for each video clip that we showed. To ensure quality we required participation qualifications as having an acceptance rate of $> 95\%$, with an experience on more than 5000 human intelligence tasks (HITs). We again restricted participation to United States-based workers.

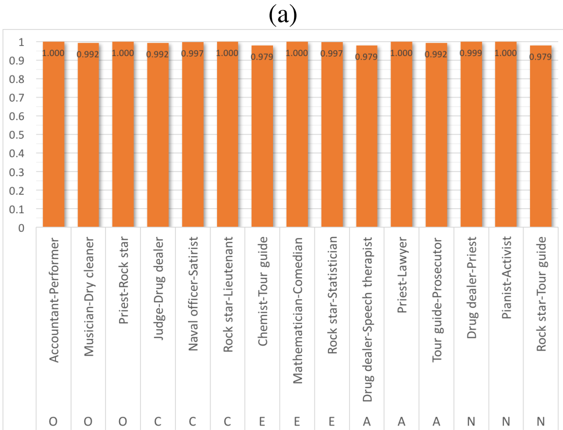
We created video clips showing two wooden mannequins aligned side by side walking for eight walk cycles with different motion styles assigned based on different stereotypes. Wooden figures were selected due to their generic nature. Since they lack gender, clothing, or age information, this restricted participants' judgments to body motions only.

We investigated the nationality and profession results independently. For each OCEAN trait, we selected three nationalities/professions featuring the highest values in that trait and paired them with three nationalities/professions featuring the lowest values in that trait. The pairing between the two ends of one trait was random. The question format was forced-choice. A question example is "Given that one animated character is an accountant and the other is a performer, which one do you think walks like an accountant?"

To analyze the results, we counted the number of different answers for each question and performed a binomial test with a null hypothesis of equally distributed answers (probability of 0.5). Fig. 4 (a,b) display the confidence levels



(a)



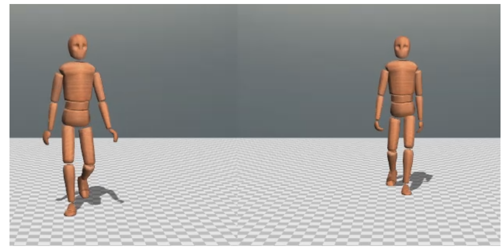
(b)

Figure 4: Evaluation results for nationality (a) and profession (b). For each OCEAN trait, there are three comparison cases. Orange bars display the statistically significant cases, blue bars display insignificant results; and the green bar displays a statistically significant case in the opposite direction.

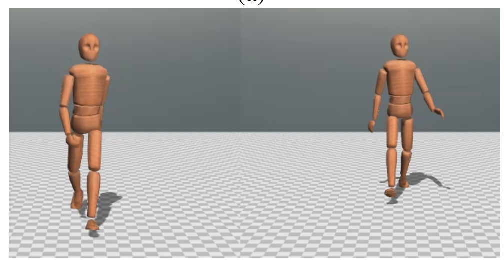
of the nationality and profession comparisons respectively. With 95% confidence level, orange bars show statistically significant results, blue bars show insignificant results and the green bar shows significant but opposite results.

Fig. 5 (a) shows the comparison case for Jamaican and Japanese stereotypes. High conscientiousness value of the Japanese stereotype constrains the arm swinging motion and the leg movements to give a more controlled and organized impression, while low conscientiousness value of the Jamaican stereotype allows a more free and less restricted appearance. Fig. 5 (b) demonstrates the comparison case for Iranian and Australian stereotypes. High openness and low neuroticism values of the Australian stereotype allow a more relaxed walking style, while low openness and high neuroticism values of the Iranian stereotype give the wooden figure faster walking speed and more frequent head movements, which may be confused as a symbol of more energetic motion.

The majority of the AMT results on nationality evaluations show that our animations fail to convey the desired impressions. On the other hand, all the profession stereotypes are distinguishable in a statistically significant manner. There may be several explanations for these results. Less known nationalities may yield less accurate OCEAN traits. Professions are generally better known and personally experienced. The motion parameters linked to each personality trait may sometimes cause confusion: e.g., faster speed is both associated with neurotic and energetic motion, or looking around oneself may both indicate openness and carelessness. To ensure generalization across experiments, we chose animations to be as context-independent as possible. However, context may be essential to draw accurate conclusions.



(a)



(b)

Figure 5: (a) Selected frame contrasting the Jamaican stereotype (left) versus Japanese stereotype (right). (b) Selected frame contrasting the Iranian stereotype (left) versus Australian stereotype (right).

Conclusions

We have presented an interface for transforming existing motions by stereotypical personality traits for different nationalities and professions. Our system simplifies the tedious task of tweaking motion parameters for each character in a game, as it automates the process of authoring stylistic motion. Our AMT experiments show that there are indeed stereotypes associated with many nationalities and professions and that they can be conveyed through motion styles. Applications extend beyond game characters to embodied agents, personal avatars, or motion picture pre-visualization.

A more comprehensive analysis will help to focus further improvements. Certain OCEAN traits may be reflected better together with other features like facial expressions; or different animation sequences other than walking may be more successful in representing nationality classes. Our environment may also be used to ”unbias” movements by setting or reducing any extremes toward the mean since we explicitly expose a stereotypical linkage between nationality, profession and personality.

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	O	C	E	A	N
accountant	-2	1.964	-1.038	0.04	-0.966
activist	1.625	0.889	2.5	-0.36	1.103
ambassador	-0.367	1.607	1.04	0.714	-0.481
animal trainer	1.25	1.556	0.667	1.111	-0.462
anthropologist	1.259	1.174	-0.92	0.333	-1.036
archaeologist	0.545	1.5	-0.962	0.385	-0.929
art dealer	1.867	0.75	1.04	1	-0.741
astronaut	2.077	2	-0.4	0.391	-0.679
attorney	-0.481	1.696	0.28	-1.375	0.407
au pair	0.464	1.107	0.423	1.28	-0.862
baker	0.773	0.929	0.269	1.556	-0.714
bank manager	-1.75	1.926	0.308	-0.24	0.034
banker	-1.458	1.852	0.083	-0.12	-0.862
businessman	-0.333	1.393	1.536	-0.318	0.231
butcher	-0.857	0.429	-0.308	-0.16	-0.414
cashier	-0.889	1.179	0.393	1.182	-0.519
ceo	0.481	1.464	0.857	-0.455	0.222
cheerleader	0.929	0	2.308	1.462	0.276
chemist	0.071	2.04	-1.769	0	-1.034
chiropractor	-0.25	1.222	-0.375	1	-0.552
comedian	1.933	0.536	2.76	0.741	-0.346
comptroller	-0.875	1.741	-0.889	-0.185	-0.385
computer expert	0.565	1.536	-1.08	0.227	-0.6
congressman	-1.31	0.333	1.25	-0.913	0.385
cosmetician	1	0.571	0.84	1.136	-0.12
cyclist	0.762	0.444	-0.125	0.407	-0.63
defense lawyer	-0.318	2.071	0.654	-1.077	0.536
designer	2.259	0.857	1.308	1.28	-0.69
dietician	0.5	1.519	-0.185	1.148	-0.885
diplomat	0.296	1.607	0.286	0.818	-0.593
doctor	0.222	2.217	0.08	1	-0.679
drug dealer	0.792	-1.333	-0.583	-2.04	1.345
drummer	2.037	-0.304	1.64	0.25	0.5
dry cleaner	-2.042	0.852	-1	0.769	-0.308
economist	-1.034	1.481	-0.583	-0.391	-0.32
entertainer	2.167	0.107	2.083	0.864	0.12
entrepreneur	2.25	1.214	1.5	0.16	0.036
financial analyst	-1.185	1.815	-0.75	-0.227	-0.222
florist	1.25	0.852	0.296	1.385	-0.577
football coach	0.321	1.56	1.92	-0.769	1
grocer	-0.621	0.259	0.458	0.773	-0.2
guitarist	2.107	-0.04	1.077	1	0.241
hotel manager	-0.75	1.481	0.5	0.76	-0.379
house decorator	1.8	1.107	1.6	1.571	-0.852
illusionist	2.103	0.444	1.042	0.826	-0.308
interpreter	0.545	1.107	-0.077	1.111	-0.857
investment banker	-0.964	2.12	-0.423	-1	0.179
judge	-1.357	2.16	-0.741	-0.885	-1.24
juggler	1.167	0.741	0.708	0.96	-0.552
juror	-0.333	1.286	-0.76	-0.179	-0.407
lawyer	-0.667	1.607	0.885	-1.792	0.345
lieutenant	-0.833	2.269	0.556	-1.074	0.077
manager	-0.833	1.393	0.76	-0.182	0
market analyst	-0.75	1.714	-0.269	-0.64	0.552
mathematician	-0.593	2	-1.643	0	-0.667
merchant	0.185	0.87	0.92	0.583	0.214
meteorologist	-0.286	0.741	0.5	1.435	-0.577
movie star	1.958	-0.107	2	0.455	0.87
musician	2.542	0.357	1.52	1.091	0.2
naval officer	-1.214	2.577	0.083	-0.522	0.115
nutritionist	-0.227	1.429	-0.308	1.037	-1.185
performer	2.444	0.261	2.12	0.667	0.25
physicist	0.963	2.174	-1.333	-0.333	-1.107
physiotherapist	0.333	1.786	-0.5	1.227	-0.815
pianist	1.567	1.357	-0.48	1.107	-1.259
politician	-0.786	-0.2	1.84	-1.692	0.207
priest	-1.875	1.704	-0.417	1.92	-1.241
prime minister	0	1.893	0.308	-0.111	0
private investigator	1.179	1.87	-1.08	-0.792	-0.321
probation officer	-1.815	1.393	-0.286	-0.864	0.231
professional dancer	2	1.8	1.731	1.192	-0.069
professor	0.625	1.654	0.583	0.68	-1.172
proscecutor	-0.407	1.607	0.357	-1.818	0.148
psychologist	0.5	1.429	-0.769	1.259	-1.214
rabbi	-1.467	1.286	0.2	1.643	-0.889
realter	-0.25	1.037	1.083	0.28	-0.379
recruiter	-0.833	1.741	1.64	0.107	0
rock star	2.542	-0.667	2.538	-0.111	1.385
runner	0.828	0.852	-0.167	0.565	-0.32
satirist	1.367	-0.357	1.12	-0.429	-0.154
scientist	1.042	2.074	-0.875	0.167	-0.897
secretary	-1.208	1.815	-0.148	0.923	-0.808
senator	-1.357	1	0.8	-1	0.48
sergeant	-1.69	2.074	1.125	-1.591	0.2
sniper	0.393	1.821	-1.462	-1.48	-0.448
sociologist	0.917	1.357	-0.125	1.182	-0.92
speech therapist	0.138	1.704	1	1.739	-1.192
statistician	-1.091	2.036	-1.5	0	-0.643
stockbroker	-1.4	1.393	0.24	-0.571	0.407
surfer	1.75	-0.16	0.615	1.308	-1.138
teller	-1.286	1.4	-0.385	0.654	-0.862
tennis coach	0.481	1.783	0.96	0.25	0
tour guide	1.136	1.25	2.538	1.852	-1.357
travel agent	0.963	0.821	1.75	1.636	-0.667
veteran	-0.667	1.593	-0.37	0.481	0.038
violinist	1.75	1.571	-0.2	1.364	-0.417
weatherman	-0.5	0.667	1.292	1.087	-0.538

Appendix. 1: AMT user ratings for profession stereotypes. Green boxes indicate statistically significant answers.

	O	C	E	A	N
Afghan	-1.129	-0.3	-0.867	-1.069	1.533
African American	0.548	-0.133	1.5	0.2	1
Albanian	-0.484	0.1	-0.533	-0.345	0.276
Algerian	-0.387	-0.167	-0.467	-0.207	0.483
American	1.452	0.533	2.267	-0.138	0.167
Angolan	-0.419	-0.345	-0.433	-0.172	0.034
Argentine	0.355	0.3	1.067	0.379	-0.2
Armenian	-0.29	0.967	-0.1	-0.179	0.333
Australian	1.806	1.1	1.933	1.586	-1.467
Austrian	1.194	1.5	0.133	0.379	-1.133
Azerbaijani	1.774	-0.233	-0.517	-0.276	0.333
Bangladeshi	-0.8	0.233	-0.8	-0.276	0.2
Batswana	-1.065	-0.552	-0.5	0.3	0.133
Belarusian	-0.355	0	-0.3	0.067	0.133
Belgian	1.161	1	-0.3	0.6	-1.167
Belizean	0.516	0.267	0.233	0.483	-0.4
Bolivian	0.129	-0.069	-0.033	0.4	0.333
Bosnian	-0.581	0.033	-0.767	-0.167	0.8
Brazilian	1.742	0.033	2.3	1.1	0.414
British	0.29	1.414	0.333	1	-1.2
Bulgarian	0.194	0.483	-0.333	0	-0.138
Burmese	-0.367	0.1	-0.9	0.067	-0.333
Cambodian	-0.065	-0.033	-0.933	0.033	0.033
Cameroonian	-0.4	-0.433	-0.633	0.4	-0.267
Canadian	1.226	1.467	0.414	1.767	-1.552
Chilean	0.613	0	0.867	0.621	-0.133
Chinese	0.419	2	-1.267	-0.6	-0.267
Colombian	0.774	0.033	1.767	0	1.267
Congolese	0.226	-0.067	-0.5	0.133	0.333
Costa Rican	0.71	0.2	1.567	0.759	-0.276
Croatian	-0.387	0.448	-0.167	0.233	0.067
Cuban	0.226	0.3	1.517	0.586	0.897
Cypriot	-0.419	0.2	-0.2	0.167	0.033
Czech	0.323	0.5	0	-0.033	0.033
Danish	1.345	1.667	-0.333	1.034	-1.2
Dominican	0.677	0.067	1.133	0.7	0.667
Dutch	1.194	1.7	-0.033	1.2	-1.3
Ecuadorean	0.226	0.333	0.467	0.9	0.25
Egyptian	-0.3	0.5	-0.033	-0.033	0.467
Estonian	-0.4	-0.033	-0.5	0.533	-0.367
Ethiopian	-0.6	-0.5	-0.5	0.586	-0.3
Finnish	1	1.133	-0.8	1.333	-1.8
French	1.333	0.367	1.2	-0.067	-0.167
Georgian	-0.133	0.367	-0.733	0.2	0.2
German	1.067	1.8	-0.333	0.2	0.333
Ghanaian	-0.467	-0.167	-0.733	0.233	-0.1
Greek	1.241	-0.3	1.933	0.667	0.5
Greenlandic	-0.032	1.1	-0.733	1.333	-1.6
Guatemalan	0.323	-0.5	0.897	0.667	-0.033
Haitian	0.129	-0.933	0.6	0.31	0.067
Hispanic American	0.613	0.533	1.567	0.7	0.9
Honduran	-0.133	-0.233	0.633	0.483	-0.333
Hungarian	0.452	0.867	-0.533	0.5	-0.533
Icelandic	0.645	1.433	-0.667	1.567	-1.633
Indian	0.4	0.6	0	0.633	-0.233
Indonesian	-0.516	0.1	-0.467	0.267	-0.3
Iranian	-1.448	-0.167	-0.467	-0.933	1.7
Iraqi	-1.355	-0.138	-0.833	-0.967	1.767
Irish	0.968	0.3	1.724	0.6	0.633
Israeli	-0.226	1	0	-0.367	0.897
Italian	1.387	0.467	2.267	0.633	0.7
Jamaican	1.387	-0.767	1.567	1.433	-0.7
Japanese	0.613	2.483	-1.533	0.4	-1.433
Jordanian	-1	0.333	-0.714	0.2	0.433
Kazakhstani	-1.097	-0.133	-0.667	0.1	0.5
Kenyan	0.065	-0.103	-0.133	0.733	-0.167
Korean	0.226	1.467	-1.033	-0.567	-0.533
Kuwaiti	-1.3	0.1	-0.733	-0.733	0.967
Kyrgyzstani	-1	0.034	-0.867	-0.067	0.2
Latvian	-0.323	0.633	-0.533	0.621	-0.517
Lebanese	-0.613	-0.133	-0.069	-0.2	0.8
Libyan	-0.839	-0.6	-0.345	-0.467	1.2
Lithuanian	0.1	0.367	-0.533	0.267	-0.133
Luxembourg	0.6	1.267	-0.31	0.467	-1.207
Macedonian	-0.226	0.2	-0.433	0.133	-0.5
Malaysian	-0.323	0.233	-0.5	0.4	-0.267
Mexican	0.548	0	1.867	0.733	0.967
Moldovan	-0.267	-0.1	-0.267	0.3	-0.467
Mongolian	-0.161	0.31	-0.833	-0.1	-0.333
Moroccan	0.226	0.6	-0.067	0.467	0.1
Mozambican	-0.548	-0.4	-0.567	0.333	-0.1
Namibian	-0.677	-0.1	-0.296	0.4	-0.31
Nepalese	-0.161	0.467	-1.333	0.759	-1.233
New Zealand	1.677	1.433	0.867	1.667	-1.567
Nicaraguan	0.065	-0.233	0.333	0.533	0.367
Nigerian	-0.452	-0.567	-0.172	0.033	0.517
North Korean	-1.581	0.9	-2.4	-1.533	0.793
Norwegian	1.267	1.4	-0.2	1.333	-1.448
Pakistani	-1.419	-0.103	-0.667	-0.759	1.786
Palestinian	-1.484	0	-0.567	-0.6	1.724
Panamanian	0.387	0.172	0.467	0.655	-0.5
Papua New Guinean	-0.097	-0.033	-0.767	0.867	-0.69
Paraguayan	0.129	0.345	0.333	0.533	-0.667
Peruvian	0.194	0.517	0.6	0.4	-0.433
Philippine	0.516	0.533	-0.1	0.733	-0.133
Polish	0.452	0.5	0.467	0.241	-0.167
Portuguese	1.032	0.5	0.833	0.767	-0.067
Puerto Rican	1.258	0.233	2.133	0.833	1.367
Qatari	-0.968	0.233	-1	-0.067	0.167
Romanian	0.065	0.567	-0.167	-0.1	0.517
Russian	-0.194	0.833	0.533	-0.967	1.433
Rwandan	-0.677	-0.267	-0.7	0.233	0.567
Samoan	0.258	-0.267	0.414	0.933	-0.533
Saudi	-1.355	0.793	-0.767	-1	0.933
Saudi Arabian	-1.387	0.633	-0.733	-0.833	1.1
Senegalese	-0.226	-0.433	-0.759	0.467	0.3
Serbian	-0.581	-0.133	-0.067	-0.6	0.667
Sierra Leonean	-0.581	-0.033	-0.467	0.467	0.433
Singapore	0.742	1.1	-1.1	0.233	-0.759
Slovak	-0.161	0.233	-0.4	-0.167	0.133
Slovenian	-0.387	0.267	-0.467	-0.167	0.034
Somali	-0.839	-0.733	-0.2	-0.3	1
South African	0.097	0.333	0.033	0.133	0.033
South Korean	0.29	1.3	-1.167	-0.333	-0.4
Spanish	1.032	0.5	1.8	0.233	0.267
Sri Lankan	-0.258	0.133	-0.733	0.667	-0.033
Sudanese	-1.034	-0.333	-0.633	-0.241	0.867
Swedish	1.742	2	-0.1	1.633	-1.621
Swiss	1.419	1.9	-0.448	1.433	-1.833
Syrian	-1.129	-0.167	-0.6	-0.7	1.533
Taiwanese	0.71	1.367	-0.9	0.433	-0.667
Tajikistani	-0.419	0.138	-0.733	-0.2	0.172
Thai	1	0.733	-0.433	0.333	-0.621
Turkish	-0.194	0.3	0	-0.345	0.4
Ugandan	0.097	-0.533	-0.533	-0.1	0.467
Ukrainian	0.161	0.167	-0.033	-0.3	0.9
Uruguayan	0.129	-0.2	0	0.433	-0.3
Uzbekistani	-0.548	-0.034	-0.667	-0.533	0.433
Venezuelan	1.033	-0.167	1.367	0.467	0.414
Vietnamese	-0.032	1.133	-0.833	-0.133	-0.069
White American	1.516	0.633	1.167	-0.241	-0.345
Yemeni	-1.355	0.233	-1.1	-0.367	0.533
Yugoslav	-0.581	0.067	-0.5	-0.071	0.2
Zambian	-0.645	-0.433	-0.233	0.433	0
Zimbabwean	-0.419	-0.5	0	-0.033	-0.133

Appendix. 2: AMT user ratings for nationality stereotypes. Green boxes indicate statistically significant answers.