QUICK DECISIONS INVOLVING THREATENING AND NON-THREATENING IMAGES

by

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Abstract

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NON-THREATENING

IMAGES

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The purpose of this research was to investigate the role of facial expressions with respect to quick decisions involving threatening and non-threatening images, to understand better the theoretical perspectives involving the amygdala, orbitofrontal cortex, and anterior cingulate cortex. Participants completed several surveys and played a categorization game where they viewed pictures for 1.25 seconds and then made a categorizing decision of “dangerous” or “safe” based on the presence of weapons in the photo. Participants had 1 second to decide. Pictures included men, women, and children, with either angry or neutral facial expressions, holding either weapons or innocuous items. Participant’s reaction time was recorded. It was hypothesized that dangerous pictures would be categorized more quickly and accurately than safe and angry pictures more quickly and accurately than pictures with neutral expressions. It was also hypothesized that there would be an interaction between the categories. Main effects of object held (dangerous or safe) were found for both reaction times and accuracy rates. A main effect was found for facial expression with respect to accuracy rate. Interaction effects were also found for object held by facial expression with respect to both reaction times and accuracy rates. Analyses revealed that dangerous pictures were more

accurately and quickly categorized than safe pictures and angry pictures were the least accurately categorized. These results provide some evidence that an actor-critic structure may exist. Furthermore, these results indicate that facial expressions influence the categorization of safe and dangerous situations.

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Chapter 1

Introduction

Correct categorization of dangerous situations is important in every day decision making. The ability to differentiate between a pedestrian and a mugger is vital for survival. For police officers, ascertaining the difference between potentially dangerous criminals and nonviolent criminals can be the difference between life and death for both the officer and the civilian. With recent shootings of unarmed civilians by the police in the news, it is important to understand the aspects involved in the determination of safe and dangerous situations.

Also, military personnel are trained extensively in combat techniques which are then used in a time of war where differentiation between the enemy and noncombatants is crucial. Therefore, being able to determine quickly the difference between safe and dangerous people and situations has its evolutionary advantage: survival.

Thus, this thesis investigated reaction times and accuracy rates of quick decisions involving the categorization of pictures as dangerous or safe based on the presence of weapons. Furthermore, reaction times and accuracy rates were analyzed with respect to the facial expressions of persons in the pictures to determine the role emotion plays in the categorization of safe and dangerous images.

Understanding Categorization

How do people classify situations or objects? Piaget and Inhelder (1969) describe “schemas” which are categories that allow humans to sort cognitive and sensory information into groups. It is from this that the ideas of assimilation and accommodation are derived; where assimilation is the categorization of new information into existing categories, and accommodation is the process of creating new categories when information does not fit into old categories (Piaget & Inhelder, 1969).

From a very young age, children learn to organize their world by categorization and classification. As Piaget and Inhelder (1969) explained, children at the pre-operational stage (ages 2-7) are able to sort objects into like groups as long as they sort one group at a time. As children enter into the concrete operational stage (ages 7-11), they are able to sort multiple groups at the same time. When the child reaches the formal operational stage (ages 12 and up), they are able to understand hierarchical classification involving superordinate and subordinate classes (Piaget & Inhelder, 1969).

The ability to categorize situations by their similar aspects is useful to humans because it allows for the grouping of sensory input which increases the amount of information that can be learned and remembered. Being able to remember more means that we can use previously gained knowledge and apply it to new situations.

Most often, people classify situations or objects by visual cues. Objects may be classified by aesthetics (color, shape, etc.) and purpose (transportation, cleaning, etc.), while people are classified by a number of social markers such as age or clothing (Quinn & Rosenthal, 2012). However, for threatening or fearful situations, people may be classified by emotional facial expressions, via the amygdala (Adolphs, 2002; Williams, McGlone, Abbot, & Mattingley, 2004).

Brain Areas Involved in Specific Categorization

The amygdala is located in the part of the brain known as the limbic system. It is responsible for encoding and retrieving emotional memories, often related to reinforcement learning (rewards or punishments given at the same time a stimulus is presented) (Reece, Urry, Cain, Wasserman, Minorsky, & Jackson, 2009). With classification, the amygdala assists in coding possible choices into memory as high emotion or low emotion, which are aspects the orbitofrontal cortex selectively attends to in the categorization process.

The orbitofrontal cortex then categorizes these choices based on their attributes the amygdala gives them, with selective attention given towards the more important attribute, which are weighted more heavily (Levine, 2012). The orbitofrontal cortex is located in the frontal lobe, specifically, the prefrontal cortex (Reece et al. 2009). It is thought to be related to reward in reinforcement learning, and memory in decision making (Cavada & Schultz, 2000).

If any conflict is found when deciding between two choices, the anterior cingulate cortex is responsible for detecting it. The anterior cingulate cortex rests above and next to the corpus callosum. It inhibits impulsive or natural responses, in favor of a thoughtfully correct response (Stevens, Hurley, Hayman, & Taber, 2011). Take for example, the Stroop task. When asked to name the color of ink a word is printed in, instead of reading the word, the anterior cingulate cortex detects conflict when the word is “Green” but is typed in red ink (Braver, Barch, Gray, Molfese, & Snyder, 2001). See Figure 1-1 for illustration of brain regions.

This may also be the case if conflict arises during categorization of choices. For instance, when making a decision between safe and dangerous looking pictures, the natural tendency may be to selectively attend to angry facial expressions and impulsively categorize any picture with such as dangerous. However, if a safe picture is shown with an angry face, this could cause wrongful categorization. If this happens, the anterior cingulate cortex may act as a type of “reset” in which the choice needs to be categorized into a different category or a new category needs to be made altogether.

The amygdala, orbitofrontal cortex, and the anterior cingulate cortex work together to selectively attend to important aspects of the options available, classify options based on their attributes, and detect mismatches between attributes of the options and categorization, which allows for decision making to happen, (Levine, 2012).

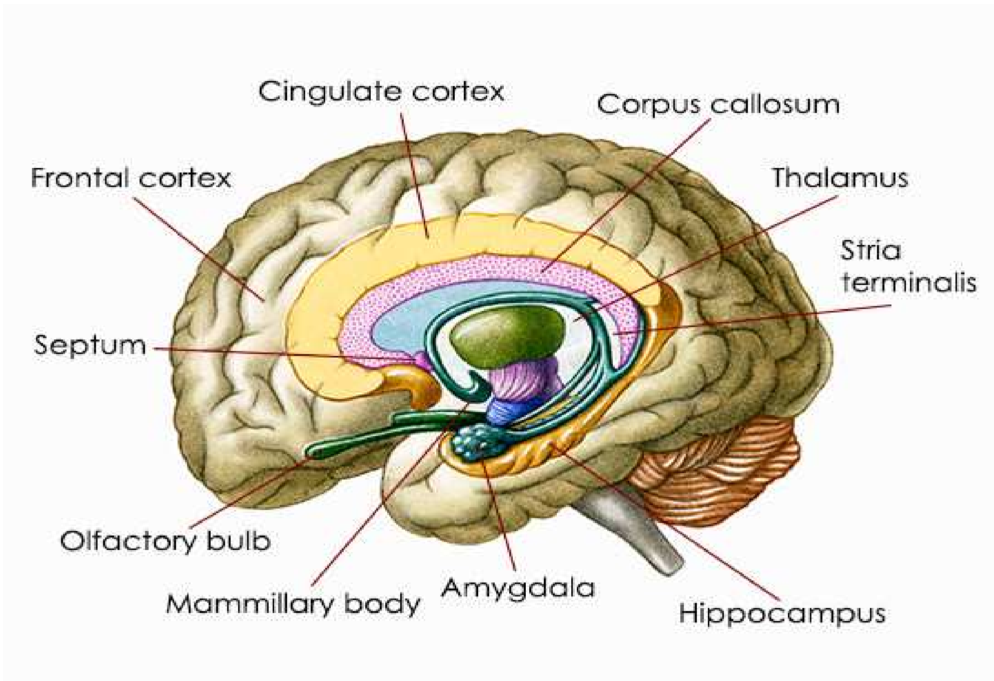


Figure 1-1 Amygdala, OFC, and ACC (Buzzle, 2014)

Reinforcement Learning in Engineering

Interestingly, neural network mathematical models of this decision making process are closely related to engineering mathematical models of adaptive dynamic programming, via reinforcement learning (Lewis & Vrabie, 2009). Reinforcement learning began with the idea of operant conditioning brought about by Thorndike and Skinner in the field of psychology.

Thorndike's Law of Effect proposed that with experience, over time, pleasant outcomes will produce more of the same behavior, while unpleasant outcomes will produce less of the behavior (Thorndike, 1898). Thorndike drew his conclusion from watching cats break out of puzzle boxes. After the cat learned the escape route and the buttons to push to make the door of the puzzle box open, the cat escaped faster each time. B.F. Skinner is known for operant conditioning as well. He designed “Skinner Boxes” in which animals were kept for a specific amount of time. While in the Skinner box, the animal would experience positive and negative reinforcement and punishment for their actions (Skinner, 1950).

Thorndike and Skinner paved the way for the role of operant conditioning, a psychological process in which a person or animal’s behavior is changed based on rewards and punishments of those actions. Grounded on this concept, the engineering view of reinforcement learning arose, suggesting that people and machines learn by interacting with their environment in a trial and error fashion (Sutton & Barto, 1998).

In the engineering view of reinforcement learning, the “learner” is not told what to do and has no specific set of actions to carry out, only an end goal to achieve (which is solving a given problem). Furthermore, the “learner” may receive rewards immediately after an action or the “learner” may receive rewards later on. Figuring out the most efficient way to achieve the goal is the reinforcement learning method. The two most important aspects of reinforcement learning are: the trial and error process and the delayed rewards (Sutton & Barto, 1998).

A child throwing a baseball in the back yard is one example of reinforcement learning (Rosenstein & Barto, 2004). The child may aim at a specific fence-post and with every throw feedback is given to the child from the environment. The child’s goal is to hit the fence post, but if the ball lands too far to the right, the child has to adjust the way he or she throws to land the ball slightly more to the left. Eventually, the child learns how to throw a baseball by trial and error through experience from reinforcement given by the environment.

Teaching a dog to sit is another example of reinforcement learning. The owner verbally commands the dog to “Sit!” and when the dog sits, the owner rewards the dog with a treat. The dog does not actually know what the owner wants; however through the trial-and-error process, the dog finds that when he performs the sitting behavior, he receives a tasty treat.

On the other hand, supervised learning differs from reinforcement learning in that the “learner” has one specific goal to achieve and does not have to figure out how to achieve the goal through trial-and-error; a “teacher” supervises the process, making suggestions on how to improve (Rosenstein & Barto, 2004). Furthermore, the “learner” in reinforcement learning has to select the choices to be made whereas in supervised learning, the “teacher” informs the “learner” on how to improve the choices that were made (Barto, Sutton, & Anderson, 1983). In reinforcement learning, the decision-maker looks at the choices already made to figure out what choices to make next, which differs from supervised learning in that the “teacher” tells the decision maker what the correct choice should have been.

Unfortunately, reinforcement learning and supervised learning both have their downsides (Sutton & Barto, 1998). In the instance of a robot learning to stand on its own feet after falling over, it would take hundreds of trials to learn such a task by reinforcement learning alone, and this is not always optimal. Whereas in the instance of a computer learning to have a conversation, it is impractical to have examples of every type of conversation stored in its data base, nor is it realistic, which is the case with supervised learning (Sutton & Barto, 1998).

Adaptive Dynamic Programming

Interestingly, reinforcement learning has been generalized to different aspects of science including control theory, information theory, and dynamic programming. Dynamic programming refers to a concept in which large mathematical problems are solved by breaking them down into smaller problems which are more easily managed. The smaller pieces are then solved using an iterative method until the optimal solution is revealed.

Interestingly, there is a point in dynamic programming in which a specific equation that has to be used, is found to be insolvable due to the limited discrete values allowed in the equation, and this is not-so-jovially referred to as the “Curse of Dimensionality” (Wang, Zhang, & Liu, 2009, Lewis & Vrabie, 2009). To overcome this issue, a concept introduced as a “critic” is used to approximate the piece of the equation that is insolvable, by using neural networks, thus lending an approximate dynamic programming solution. Therefore, this process is referred to as adaptive dynamic programming (Wang, Zhang, & Liu, 2009).

Adaptive dynamic programming differs from dynamic programming in that it does not need to know system dynamics (the environment), it is an on-line, forward-in-time procedure, and deals with learning in real-time. Dynamic programming, on the other hand, uses off-line planning which is not learning in real-time, the system dynamics need to be known, and it is a backwards-in-time procedure (Lewis & Vrabie, 2009).

Actor-Critic Structures

Specifically, in adaptive dynamic programming, reinforcement learning takes place through the actor-critic relationship established with mathematical formulas. The actor-critic structure (Barto, Sutton, & Anderson, 1983) embodies reinforcement learning through a trial and error process in which the actor (learner) interacts with the environment to achieve specific goals. These specific goals are called the “policy structure”. The actor chooses how to accomplish these goals through actions which are the “policy”. The critic evaluates each action to determine how close the actor has come to the goal through a reward function and a value function (Lewis & Vrabie, 2009). A reward function is the immediate reward which occurs directly after an action, whereas the value function is the total reward in the long run (Sutton & Barto, 1983).

This is a two-step process involving policy evaluation and policy improvement. Policy evaluation is determining how close the actions have achieved the goal based on the rewards. Policy improvement is the adjusting of the actions by the actor to improve the reward. This involves an iterative process by which evaluations and updates occur. After the actor implements the new policy (actions) the process starts over with re-evaluation and then re-updating (Lewis & Vrabie, 2009).

To illustrate this process with a human example, suppose the actor is a college student, the critic is environmental cues, and the goal is to complete homework. The college student chooses to work on their homework in front of the TV (this is the policy or action). After an hour, the college student looks at their progress (policy evaluation). The college student notices that only two homework problems have been completed out of 15 (reward observation). For this immediate instance in time (reward function), this is fine, but in the long term (value function), and at this rate, it would take the college student over seven hours to complete it. Therefore, the college student decides to turn the TV off to be able to finish more quickly (critique on how to improve). Thus, the college student turns the TV off (policy improvement) and continues working on the homework. Another hour passes and the process is repeated by checking how many homework problems have been completed. After time, successful policies should be remembered because of the association made between the action and the reward (Lewis & Vrabie, 2009).

Therefore, past experiences should be able to be used as blueprints for similar future decisions (Sutton & Barto, 1983).

If actor-critic structures can be found in the brain, then neural network models of those brain regions could be used to approximate the value function (the piece of the insolvable equation), thus bypassing the “Curse of Dimensionality”. From this originates the idea that by combining adaptive dynamic programming and neural networking, actor-critic brain structures could be used to solve reinforcement learning problems. Therefore, with a specific neural network in mind it may be possible to test behaviorally with a categorization game, whether the neural network would work as an actor-critic structure in reinforcement learning.

Neural Networks and Categorization

One possible neural network has been found in Levine (2012). Fascinatingly, this neural network model looks at the role of emotion on choices that are probabilistic with brain regions involving the amygdala, orbitofrontal cortex, ventral striatum, thalamus, anterior cingulate cortex, and premotor cortices. Human decision making is described in this model as both rational (based on numerical judgments that are correct) and irrational (judgments based on emotion that are often biased) (Levine, 2012). As an example, suppose a choice is given to participants of 50 dollars or a romantic kiss from their favorite movie star. Rottenstreich and Hsee (2001) found that 70% would rather have the money. However, when participants were given a choice of a 1% probability of 50 dollars or a 1% probability of a romantic kiss from their favorite movie star, they found that 65% chose the kiss.

To explain this, researchers have found that people tend to overweight small probabilities (1%) when the choice is high in emotion (romantic kiss) (Tversky &

Kahneman, 1981). Fuzzy Trace Theory is the idea that situations are encoded into memory by two different avenues: verbatim and gist. When humans encode information into memory using verbatim, exact details or words are remembered, when encoding using gist, the general idea is remembered (Brainerd & Reyna, 2002). Therefore, Fuzzy Trace Theory explains the overweighting of small probabilities by the way participants encode the data (Reyna & Brainerd 1991). To elaborate, Reyna and Brainerd (1991) suggest that participants encode the general idea (gist) of 1% probability as “not much of a chance of it happening”, therefore, they are more likely to choose the choice that is emotionally laden (the kiss).

Intriguingly, Levine (2012) models this data in a neural network. When given the choice above, it is suggested that the amygdala codes each of the options into memory as high in emotion or low in emotion thus aiding in attentional selection of the attributes of the choices. The orbitofrontal cortex codes the gist of the options into memory as the “possibility of a gain” versus “1% probability of a gain” or “no possibility of a gain”. Therefore, the kiss option is emotionally laden and will be placed in the “possibility of a gain” category whereas the money option is not very emotional and as such will be placed into the “1% probability of a gain” category. This is executed by the orbitofrontal cortex (Levine, 2012). Matching them correctly relies on amygdalar signals to the anterior cingulate cortex. If there is a mismatch, the anterior cingulate cortex detects it. Through this model, it is possible to see the connection between the actor-critic structure and neural networks. It is suggested that the amygdala and orbitofrontal cortex may work together as an actor and the anterior cingulate cortex may work as a critic.

Fascinatingly, Levine (2012) is the first step at fusing adaptive resonance theory and fuzzy trace theory. Adaptive resonance theory, also known as ART, describes the human process of categorizing information through supervised and unsupervised reinforcement learning neural networks. When categorizing incoming information, a "match-based" type of learning occurs. Sensory information is compared with the expectations of already stored similar information in the memory which is also known as a "prototype". The sensory information is processed "bottom up" while the expectation or prototype is processed "top down". If the sensory information is similar enough to the prototype, then the two converge and is considered a "match" which can be categorized as being in that class. For instance, if a student sees an object that is rectangular, hard on the top and bottom, with paper in the middle, then it is close enough to match the prototype of book. Different sizes, colors, and other aspects of books encountered can be added to the memory of the prototype to allow for better future matches. However, if a student comes across a very long sheet of paper rolled up that is not very close to the prototype book, then a reset happens where a new prototype is selected and the process of matching continues (Carpenter & Grossberg, 2003).

Combining Ideas of Categorization, Engineering, and Neural Networks

Actor-critic structures involve a two part reinforcement learning system with the actor as the "learner" and the critic as the "evaluator". The learner attempts to reach a goal through trial and error while the critic gives information on how close the learner is to the goal. When an actor-critic structure is found in the brain and written up as a neural network, the mathematical model can be used by engineers to solve their own mathematical reinforcement learning problems. With Levine's 2012 neural network model, it is possible that the actor consists of the teamwork of the amygdala and the orbitofrontal cortex working together. The amygdala and the OFC may categorize incoming emotional information. The anterior cingulate cortex possibly evaluates the job of the amygdala and OFC by checking for matches and mismatches in categorization, and therefore, explaining when the actor is close to reaching the goal, or far away from reaching the goal. With this in mind, it may be possible to lend credence to this theory by testing the reaction times of participants when categorizing emotional and non-emotional pictures. Since the nature of this neural hypothesis deals directly with perceptual categorization, testing it behaviorally will consist of simply measuring categorizing response times and accuracy rates. This way, engineers will have a better idea if using this specific mathematical neural network will help solve their reinforcement learning problems.

Similar Research

Lamberts (2000) explain that perceptual categorization is the grouping of visually presented stimuli and has been used in many aspects of psychology including memory and recognition (Estes, 1994; Nosofsky, 1991), categorization and attention (Bundesen, 1990), and object recognition (Logothetis & Sheinberg, 1996).

In the field of psychology, Estes (1994) uses neural network models to explain category learning, recall, and recognition. Nosofsky (1991) investigates how well participants detect the similarity of items and discriminate between their differences using perceptual categorization, while Bundesen (1990) explains that perceptual categorization consists of recognizing an object visually and being able to selectively attend to it. Logothetis and Sheinberg (1996) show that in order to perceptually categorize, object recognition must first occur.

From above, it is evident that perceptual categorization relies on the ability to selectively attend to an item, recognize it, and recall it from memory. Interestingly and as previously stated, the amygdala encodes visual stimuli into memory as highly emotional or low emotion, and the orbitofrontal cortex selectively attends to important attributes of the visual stimuli to correctly categorize them. The anterior cingulate cortex then detects any conflict found in the categorization process. Refer to Figure 1-2 for further illustration.

Lamberts (2000) also explains that in the past, response times have been used to understand the classification process (Jolicoeur, Gluck, & Kosslyn, 1984; Rosch, 1973). Jolicoeur et al. (1984) investigated whether superordinate classifications would take longer to name than basic level classifications. On the other hand, Rosch (1973) found that people have shorter response times to categorizing things that match the prototype than for things that are not close to the prototype.

In general, people can classify or categorize pictures into groups at an average speed, but if the picture or object is of an unexpected group, falls on the fuzzy edge of two categories, or is not representative of the prototype, then the reaction time for categorization will slow down (increase in its numerical value).

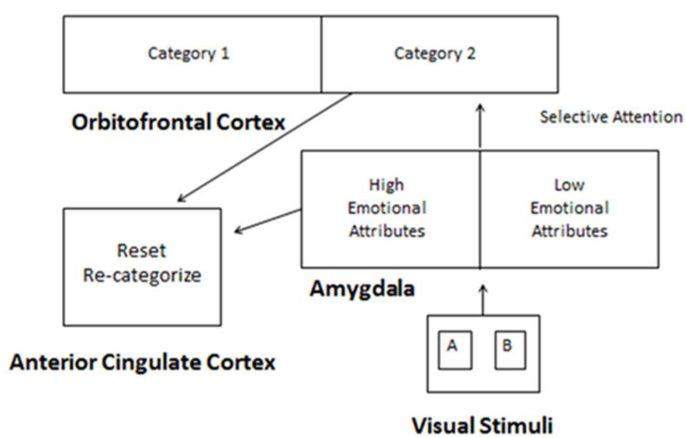


Figure 1-2 Flow Chart of Brain Interactions

Therefore, if participants are asked to categorize pictures, one at a time, into safe or dangerous categories based on the emotional facial expressions and the attributes of weapons present or no weapons respectively, it is possible that the amygdala and OFC will work together to correctly categorize pictures at the average response time. However, when there is conflict with the picture such as an angry facial expression on a person holding a blow-dryer instead of a gun, the anterior cingulate cortex will act as the critic, slowing the decision making process down to correctly categorize or invent a new category for the picture. See Figure 1-3 for further illustration of this idea.

In other words, the amygdala encodes the pictures into memory based on the emotional content as high affect or low affect. The OFC then takes the information gathered from the amygdala (i.e. high emotion or low emotion) and chooses the correct category to place the picture (safe or dangerous) based on the attributes of the facial expressions and the object held (weapons or no weapons). During this process, the ACC detects conflict with respect to changes in the pictures. Since people may have an automatic amygdalar response to angry facial expressions, the amygdala should encode emotional stimuli more quickly than non-emotional stimuli. Since participants were asked to consciously decide whether the pictures were safe or dangerous, they should have selectively attended to the presence of weapons via the weapon focus effect and the "gist" was that any picture without a weapon was safe (Steblay, 1992). Therefore, it should take longer to categorize pictures that show an angry person holding something similar to a weapon, but that is, in fact not a weapon (e.g. blow dryer) because the anterior cingulate cortex slows down the categorization processes in the event of novel and strange information.

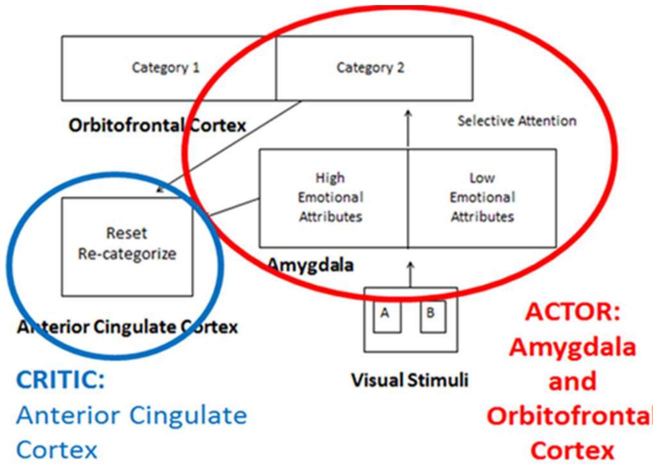


Figure 1-3 Actor-Critic Structure

Williams, McGlone, Abbot, and Mattingley (2004) looked at the amygdala in response to pictures of facial expressions and houses using fMRI. The pictures were of faces overlaid with houses. In other words, a picture of a face had a picture of a house transposed over it. Half of the participants were asked to pay attention only to the faces while the other half were asked to pay attention to the houses. Interestingly, they found that those who paid attention to the houses had greater activity in the amygdala when the face in the picture had a fearful expression. Likewise, they also found that those who selectively attended to the faces had more activity in the amygdala when the facial expression was happy. The current study will look at response time comparing the categorization of safe and dangerous images based on the presence of weapons, therefore unconsciously viewing the facial expressions.

In one study conducted by Manguno-Mire, Constans, and Geer (2005) participants who were anxious and not anxious were asked to categorize words as either “dangerous” or “safe”. In the “masked” condition, pictures of words were shown at 14 ms, which was below the conscious threshold. Those who were anxious more accurately categorized “dangerous” words while those who were not anxious more accurately categorized “safe” words. However, for the “unmasked” condition, the participants were shown the picture until he or she made a decision. Therefore, with an unlimited amount of time to look at the picture of the word and make a decision, most correctly classified the pictures, thus showing no differences between anxious and not-anxious folks. The current study will specifically investigate that middle ground: fast (1 second) decisions that are made when an image is presented just at the conscious level (1.25 s). At this level, participants will have enough time to see the image and make a quick decision, but not enough time to memorize the image or debate which decision to make, therefore, it is expected that all participants will consciously classify threatening images more quickly than non-threatening images regardless of anxiety type.

Genschow, Florack, and Wanke (2013) conducted a study in which participants were asked to press the space bar of a computer keyboard when they recognized either a spider (dangerous stimulus) or a butterfly (safe stimulus) in a string of images. In this study, the picture remained on the screen until the participant made a decision, at which time the picture was then zoomed in on. They found that dangerous stimuli (spiders) were recognized more quickly than safe stimuli (butterflies). With the present study, the participants were expected to make a categorizing decision in 1s or less after viewing the image for only 1.25s. This investigated how participants make fast decisions consciously but with little information.

Hypotheses

In support of the idea that the amygdala and OFC classify emotional stimuli more quickly than non-emotional stimuli, it was hypothesized that dangerous pictures would be classified more quickly and accurately than safe pictures and pictures showing angry facial expressions would be classified more quickly and accurately than pictures with neutral facial expressions.

Furthermore, the stimuli in the current study consisted of both facial expressions (angry or neutral) and held objects (weapons or innocuous items) which may conflict with one another. Therefore, in support of the ACC identifying conflict during the categorization process, it was hypothesized that there would be an interaction between facial expression and object held . Dangerous-angry (weapons present) pictures were expected to be classified more quickly and accurately than safe-angry pictures. Also, safe-neutral pictures were expected to be classified more quickly and accurately than dangerous-neutral. However, it was expected that the difference between safe-angry and safe-neutral pictures would have a smaller reaction time than the difference between dangerous-angry and dangerous-neutral pictures.

The Importance of this Research

This research is important due to its military, law enforcement, and psychological applications. Mathematical models of decision making can be used to implement adaptive dynamic programming in unmanned vehicles and robots. If there was support for an actor-critic structure in a neural network, then the neural network model could be used in adaptive dynamic programming.

With so many variables to consider when making a decision, it would be next to impossible for humans to reach an optimal answer. Deciding what to eat for dinner would become a daunting task if we took into account all the different variables that we would need to consider to come up with an optimal solution: time, money, gas, types of food, distance, atmosphere of the restaurant, weather, etc. However, most humans have avoided this never-ending indecisiveness by satisfying the most important attributes.

Specifically for the dinner problem, the amount of money it costs may be the attribute that is weighted most heavily, with types of food next, and the amount of time it would take to get there last. Based on these attributes alone, humans tend to make a quick decision (fast satisficing) that may not be optimal but is the best solution given the most important attributes. Understanding how fast satisficing operates will help robotics engineers apply this idea to autonomous systems that do not have the time to come to an optimal solution.

Quick, accurate decision making is also very important to law enforcement agencies. Unfortunately, humans do make mistakes, and in dangerous situations where a split second decision is needed, humans often rely on heuristics to make life changing choices. As seen in the news, the decision to shoot or not shoot a potentially armed suspect can be erroneous, leading to unarmed men being shot and (sometimes) innocent lives being taken. That is why it is important to understand how humans categorize safe and dangerous situations to be able to pinpoint inaccuracies in judgment and possibly come up with training that can correct the tendency to rely on heuristics when making a life altering decision.

Furthermore, this research is important due to its psychological applications. Categorization in itself is very important and useful in the areas of neural networks, social, learning, and cognitive psychology. Humans build and organize the world around them by categorizing sensory information. Knowing how people construct their personal worlds, can be applied mathematically to neural networks, generally to social and learning situations, and to understanding how people think. This information can then be used in computer programming, software, and robotics.

The purpose of this study was to investigate behaviorally the actor-critic structure in the neural network model involving the amygdala, orbitofrontal cortex, and the anterior cingulate cortex with a categorization game. Furthermore, it was of interest to investigate how the amygdala, OFC, and the anterior cingulate cortex work together in time-inhibited decision making processes that involve emotional cues. In past research, categorization of information has been studied in a multitude of ways except with regards to an actor-critic explanation of brain functioning. Categorization has not been looked at behaviorally through an actor-critic explanation of the workings of the amygdala, OFC, and ACC. Furthermore, many studies have involved the investigation of racial bias with facial expressions and danger (Correll, 2005; Kubota & Ito, 2014), racial bias and danger (Kenworthy et al., 2011, Correll et al. 2014; Peruche & Plant, 2006), and facial expression and attention (Lassalle & Itier, 2013; Neath, Nilsen, Gittsovich, & Itier, 2013, Rigato, Memon, Di Gangi, George, & Farroni, 2013; Williams, McGlone, Abbot, and Mattingley, 2004). However, no research has yet investigated just the influence of facial expressions on the categorization of threatening situations. Real world implications include better decision-making under pressure for humans and autonomous systems along with better understanding of the mechanisms involved when categorizing safe and dangerous situations.

Chapter 2

Method

Participants

A power analysis was conducted using Gpower (Faul, Erdfelder, Lang, & Buchner, 2007) to investigate the total number of participants needed for a repeated measures experiment. The power analysis indicated a total sample size of 148 participants to detect a small effect (f = .15) with 95% power and an alpha of .05. Therefore, a total of 151 participants were recruited from UTA's subject pool. Ethnic composition of the students included 16.7% African American, 27.1% Latino/Hispanic, 16.7% Asian, 4.2% Middle Eastern, 28.5% white and 6.8% indicating more than one ethnic composition. The sample consisted of 39.6% male and 60.4% female students, with the average student age range approximately 18 to 28 years.

Recruitment

All undergraduate students enrolled in an introductory psychology class must either participate in research through SONA or write up reviews of research articles. Therefore, participants were recruited through UTA's online subject pool (SONA). All of the participants received course research credit corresponding to one hour in-lab participation (1.5 credits). All data were collected in room 422 of the Life Science building. Participants were allowed to quit the experiment at any time which met IRB protocol.

Measures

The goal of this research was to investigate reaction times and accuracy rates for safe versus dangerous pictures involving angry or neutral facial expressions. To assess dangerousness, safeness, angriness, and neutrality of pictures, several laboratory assistants rated each picture. The resulting pictures were then used in the computer game that participants played.

To rule out extraneous factors when looking at differences in reaction time within the categorization game, participants' demographics (vision, handedness, video game usage, and military experience) and anxiety were examined. As for demographics, problems with vision could greatly influence results. We also wanted to assess difference in reaction times between military personnel and civilians, video gamers and non-video gamers. As for anxiety, research has shown in the past that on masked trials, highly anxious participants classified threatening stimuli more correctly than non-anxious individuals, and non-anxious participants classified non-threatening stimuli more correctly than highly anxious individuals (Manguno-Mire, Constans, & Geer, 2005). Also, individual differences in a person's maximizing tendency might have an effect on reaction times. Satisficing is the tendency to come up with a quick solution they may not be optimal but is "good enough". Maximizing on the other hand is the tendency to come up with an "optimal" solution at the expense of time. Therefore, it was important to investigate whether satisficers make quicker, less accurate decisions than maximizers. Lastly, in light of evidence that people can make unconscious decisions based on racial bias (Kenworthy et al. 2011), the current study looks to control for racial bias and investigate fast decision-making at a conscious level. It was important to assess for these traits to understand if they play a role in differences in reaction times for threatening and non-threatening stimuli.

Picture Rating

Picture Gathering

Pictures, (n = 324) of people with angry or neutral facial expressions holding weapons (guns, grenades, rockets, etc.) or non-essential items (soda cans, blow-dryers, vacuums, etc.) were downloaded from the internet (specifically Google). Each picture was investigated for copyright markings and discarded if any were found.

Rating of Pictures

Laboratory assistants (n = 7) rated each individual picture (n = 324) on two dimensions: facial expression and object held (safeness or dangerousness). Pictures were first divided into two categories on the computer program: dangerousness and safeness. Pictures with people holding weapons were placed in the “dangerous” category. Laboratory assistants rated these on a scale of 1(not dangerous at all) to 10(very dangerous). Next, pictures with people holding innocuous items were placed in the “safe” category. Laboratory assistants rated these on a scale of 1(very safe) to 10(not safe at all). Then the same pictures were divided into two different categories based on their facial expression: angry or neutral. For pictures with people expressing anger, ratings consisted of 1 (not angry at all) to 10 (very angry). For pictures with people showing a neutral facial expression, ratings consisted of 1 (very neutral) to 10 (not neutral at all). The means for each of the pictures were gathered. Because each picture consisted of two categories, (dangerous-angry, dangerous-neutral, safe-angry, safe-neutral) pictures were gathered by their dual ratings. The top thirty rated pictures in both the angry and dangerous group were used in the computer game. Thirty pictures rated highly for the dangerous category and lowly in the neutral category were used for the computer game. Likewise, thirty pictures which were rated lowly in the safe category and highly in the angry category were used. Lastly, thirty pictures rated lowly in both safe and neutral categories were used as well, totaling 120 pictures for the categorization game. Of the pictures used in the categorization game, mean ratings were gathered for each category; dangerous (M = 7.25, SD = 1.29), safe (M = 3.04, SD = 1.55), angry (M = 7.13, SD = 1.11), and neutral (M = 3.29, SD = 1.12).

Demographic Survey

The demographic survey examined 7 individual characteristics of the participants: gender, military experience, ethnicity, handedness, vision, age range, and video game usage.

Anxiety Survey

Generalized Anxiety Disorder (GAD-7)

The GAD-7 (Spitzer, Williams, & Kroenke, 1995) examines anxiety levels (mild to severe) by assessing how often the 7 anxiety-related symptoms occur over a two week period (α = .87). Each symptom can be rated from 0 (not at all) to 3 (nearly every day). Anxiety scores range from 0 to 21, computed by adding all ratings of symptoms together. Sample symptom items include, “Feeling nervous, anxious, or on edge”, “Trouble relaxing”, and “Becoming easily annoyed or irritable”.

Maximization Survey

Maximization Inventory

The Maximization Inventory (Turner, Rim, Betz, & Nygren, 2012) examined the participants’ tendency to find the best possible solution. Three subscales make up the Maximization Inventory: satisficing, decision difficulty, and alternative search. Satisficing (α = .77) assessed the participants’ tendency to come up with a solution that was “good enough” and consisted of 10 items. Decision difficulty (α = .86) investigated how much difficulty the participant encountered when making decisions and consisted of 12 items. Alternative search (α = .87) assessed the participants’ tendency to employ an exhaustive search when looking for an answer and consisted of 12 items. Sample items for satisficing include, “At some point you need to make a decision about things”, “There are usually several good options in a decision situation”, and “I accept that life often has uncertainty”. Sample items for decision difficulty include: “I am usually worried about making a wrong decision”, “I often experience buyer’s remorse”, and “I often change my mind several times before making a decision”. Sample items for alternative search include: “I take time to read the whole menu when dining out”, I find myself going to many different stores before finding the thing I want”, and “I take the time to consider all alternatives before making a decision”. Each item was rated on a Likert type scale from 1 (Strongly Disagree) to 6 (Strongly Agree). Scoring included averaging the items for each section: satisficing, decision difficulty, and alternative search.

Experiment

The Categorization Game

The experiment consisted of a computer game in E-prime involving the categorization of pictures as “dangerous” or “safe”. A computer game was borrowed and modified from Kenworthy et al. (2011) to suit our specific needs.

Kenworthy et al.’s (2011) shoot-no shoot task consisted of an E-prime program similar to the game used by Correll, Park, Judd, and Wittenbrink (2002). In the shoot-no shoot E-prime program, pictures were shown to participants of Black or White people holding a silver or black gun and Black or White people holding a soda can or a cell phone. Therefore, participants (all Caucasian) saw pictures of Black or White people holding guns or innocuous items. The control condition pictures in this E-prime game consisted of landscapes. All of the pictures were shown one at a time to participants in random order, and participants had no more than .80 s to make a decision to “shoot” or “not shoot”. Therefore, this looked at a participant’s automatic processing or unconscious decision making. A “shoot” decision occurred when the participant pressed the “S” on the keyboard while a “no shoot” decision occurred when the participant pressed the “L” on the computer keyboard. Participants were instructed to “shoot” when a gun was present in the photo and to “not shoot” when a gun was not presented in the photo. Kenworthy et al. (2011) found that as White participants identified more strongly with their ingroup, they were more likely to make a “shoot” decision regarding images shown with African Americans. However, as ingroup identity strengthened, participants were not more likely to make a “shoot” decision regarding images with White Americans.

In our categorization game, pictures consisted of men, women, and children holding either weapons (guns, knives, axes, grenades, and rocket propelled grenades) or innocuous items (blow dryers, shoes, tennis rackets, guitars, phones, or mega phones). Persons in the photographs had either an angry or neutral facial expression. Pictures included people of different races such as African American, Asian, Hispanic, Middle Eastern, and White. Therefore, participants saw the same pictures (*n* = 120) of people that were dangerous or safe, with angry or neutral facial expressions. For each category: dangerous-angry, dangerous-neutral, safe-angry, and safe-neutral, there were a total of 30 pictures. Within each of those categories, there were six pictures representing each of the five racial groups. To elaborate, within the 30 pictures of the dangerous-neutral category, there were six pictures of Asians holding weapons with neutral facial expressions, six pictures of African Americans holding weapons with neutral facial expressions, six pictures of Hispanics holding weapons with neutral facial expressions and so on. For every participant, the pictures were randomized so that no one saw them in the same order.

In the beginning of the categorization game, participants read directions on the computer screen which stated, “You’re about to play a categorization game. You will be shown pictures (one at a time) on the computer screen. These pictures will contain images of people (men, women, or children), that are DANGEROUS (have weapons) or SAFE (no weapons). Your job is to categorize the pictures as DANGEROUS or SAFE. Press ‘S’ if the picture is DANGEROUS. Press ‘L’ if the picture is SAFE. DANGEROUS = guns, knives, grenades, axes, or rocket propelled grenades. SAFE = no weapons shown. Press {SPACEBAR} to continue.” After the participant pressed the space bar, a fixation cross was shown for 500 milliseconds (ms) to orient the participant; then, one picture (randomly chosen), was displayed on the computer screen for 1250ms. Next, the participants had 1000ms to make a categorizing decision by pressing “S” on the keyboard for “safe” or “L” for “dangerous”. This was counterbalanced across participants. After each decision, participants were given feedback by a visual prompt of either “Oops!” or “Correct!” along with the percentage of correct responses on the computer screen. The first 10 pictures of the game were practice and not used in any analyses. Reaction times and accuracy rates were recorded for each decision made.

Procedure

This experiment consisted of a 2 (object held) X 2 (facial expression) factorial within-participants experimental design with two dependent variables: reaction time and accuracy rate.

Upon arrival at room 422 in the Life Science building of the University of Texas at Arlington, participants were placed in their own individual room, with their own computer, and handed an informed consent. After agreeing to participate, a researcher explained to them, “The experiment consists of two surveys, a game, and then a final survey. Please pay close attention to the directions on the screen because they will change throughout the computer program. If you have any questions at any time, please let me know." Then the participants began the E-prime program which consisted of the demographic survey, GAD-7 (anxiety survey), the categorization game, and The Maximization Inventory. After completing the experiment, participants were debriefed, thanked, and given 1.5 research credits. The experiment was completed in one session. The experiment generally lasted anywhere from 15 to 35 minutes.

Chapter 3

Results

Data Screening

Data from the variables - gender, military experience, ethnicity, handedness, vision, age range, video game playing, GAD score, maximization, reaction times, accuracy rates and racial bias - were screened for implausible values, data entry errors, normality, outliers and skewedness before conducting analyses.

Categorical demographic variables - gender, military experience, ethnicity, handedness, vision, age range, and video game playing - had no missing data or implausible values.

The categorical variable GAD score consisted of the summation of participant's answers on the GAD 7 questionnaire. Then, any score from 0 to 5 was labeled "mild anxiety", scores from 6 to 10 were labeled "moderate anxiety", those from 11 to 15 were labeled "moderately severe anxiety" and scores ranging from 16 to 21 were deemed "severe anxiety" per the GAD 7 scoring guide (Spitzer, Kroenke, Williams, & Lowe, 2006). No missing data or implausible values were found for GAD score.

The Maximization Inventory consisted of three continuous subscales: satisficing, decision difficulty, and alternative search. Each subscale consisted of averaging the participant's answers to the questions pertaining to that particular subscale. No missing data or implausible values were found for satisficing, decision difficulty, or alternative search variables. Satisficing, decision difficulty, and alternative search scores were all found to be negatively skewed with several outliers. In order to reduce skewedness, all three variables were transformed by squaring the values. The squared version of satisficing scores still showed non-normality and several outliers, so a cubed transformation was attempted. The cubed transformed satisficing scores showed more normality and less outlying values, and therefore were used in subsequent analyses. However, for decision difficulty, and alternative search, the squared transformation revealed less outliers and more normality. Therefore, in subsequent analyses, the squared transformed versions of these variables were used. When using these variables in a regression, a violation of the assumptions of regression was revealed; thus, a median split was conducted on the variables. Any values above the median were labeled as “high” scores while values below the median were labeled “low” scores. This version of the variables was used in subsequent analyses.

The continuous variable reaction time consisted of four separate reaction time scores, one for each of the categories: dangerous-angry, dangerous-neutral, safe-angry, and safe-neutral. These were calculated by averaging participant’s reaction times for all of the pictures in that category. No implausible values were found for reaction times. Out of 151 participants, 7 did not play the categorization game, resulting in 4.6% missing data for each of these reaction time categories. Each reaction time category was found to be fairly normally distributed. Dangerous-angry exhibited four outliers with very slight positive skew, dangerous-neutral showed four outliers with very slight positive skew, safe-angry displayed two outliers and very slight negative skew, and safe-neutral exhibited only one outlier with very slight negative skew. Transformations of the variables revealed non-normality and more outliers. Therefore, all reaction time variables were used in their original form.

The continuous variable accuracy rate consisted of four separate accuracy rates, one for each of the categories: dangerous-angry, dangerous-neutral, safe-angry, safe-neutral. Each of these accuracy rates were calculated by summing the number of pictures categorized correctly and dividing that by the total number of pictures categorized. No implausible values were found for accuracy rates. Out of 151 participants, 7 did not play the categorization game, resulting in 4.6% missing data for each of these accuracy rate categories. Since the missing data is specifically from participants selecting NOT to play the game but participating in all other surveys, this data is classified as "missing not at random" (Tabachnik & Fidell, 2007) and is addressed further in the data screening section. Each accuracy rate category was found to be severely negatively skewed with several outliers. Transformations by squaring, cubing, and inverse-reflecting the variables resulted in slightly more normal distributions with slightly less outlying variables; however severe non-normality and outliers still existed. Therefore, deletion of the outliers was analyzed and revealed fairly normal distributions with only one outlier on the safe-neutral accuracy rate. Next, a comparison of each type of transformation for the variable accuracy rate was conducted by examining the variable in a repeated measures ANOVA. Each version of accuracy rate (original, squared, cubed, inverse-reflected, and deleted outliers) revealed the same results. Therefore, all subsequent analyses used the data with the deleted outliers for the accuracy rate variables.

The continuous variable racial bias included three versions: overall racial bias, African American racial bias, and Middle Eastern racial bias. Each out-group and in-group bias was calculated by the equation $-.5*(zH + zFA)$ separately. The variable zH equaled the total number of hits for that group divided by the total number of pictures categorized for that group, and then z-scored. The variable zFA equaled the total number of false alarms for that group divided by the total number of pictures categorized for that group, and then z-scored. Next the out-group bias was subtracted from the in-group bias to create that specific bias score. The variable overall racial bias was fairly normal with a few outliers on either side of the distribution. The variable African American racial bias was fairly normally distributed with a few outliers on either side of the distribution as well. Therefore, these two variables were analyzed using their original form. However, the variable Middle Easter racial bias was severely positively skewed with a few outliers on either side of the distribution. Exploring the data's frequencies revealed that several values of data were zero. Therefore, before a square root transformation could take place, a new variable was computed where three was added to each of the data values because square rooting a data set with values of zero does not transform the data because the square root of zero equals zero. Afterwards, the square root of the variable Middle Eastern racial bias revealed more normality and less outliers. Therefore, the square root version of Middle Eastern racial bias was used in all subsequent analyses.

Preliminary Analyses

Missing Data

Several univariate analyses of variance (ANOVAs) were conducted to determine if participants who elected not to play the categorization game (n = 7) differed from the participants who did play the game (n = 144) on anxiety and the Maximization Inventory subscales respectively.

No differences were found between participants in anxiety scores $F(1, 149) = 0.40$, $p = .53$, $n_p^2 = .003$. However, for the Maximization Inventory subscales, significant differences were found. Specifically for the satisficing subscale, participants who chose to play the game had significantly higher scores (M = 123.72, SE = 3.04) than those who chose not to play the game (M = 86.58, SE = 13.77), $F(1, 149) = 6.40$, $p = .009$, $n_p^2 = .04$. This suggests that those who chose to play the game exhibited a greater tendency to reach a "fast and dirty" solution than those who opted not to play. As for the decision difficulty subscale, no significant differences were found between participants who chose to play the categorization game and those who opted not to play $F(1, 149) = 2.89$, $p = .09$, $n_p^2 = .02$. Specifically for the alternative search subscale of the Maximization Inventory, participants who chose to play the game had significantly higher means ($M = 18.94$, $SE = 0.56$) than those who opted not to play ($M = 13.20$, $SE = 2.52$), $F(1, 149) = 4.95$, $p = .03$, $n_p^2 = .03$. This explains that those who chose to play reported the tendency to search longer for an answer, while those who opted not to play reported not searching very long for an answer.

Therefore, participants who completed the experiment in its entirety differed from those who did not, specifically on satisficing scores and alternative search scores. Those who completed the experiment showed higher tendencies of satisficing and searching for alternative answers. With this in mind, cases with data missing from the game will be deleted and not used in further analyses. This may affect the generalizability of the results with respect to maximization, leading to a sample that was higher in satisficing and alternative search scores.

Gender

Two 2 (object held) X 2 (facial expression) repeated measures mixed ANOVAs analyzed the effects of gender differences on reaction times and accuracy rates. Box's M was significant, $p = .03$. Levene's test was significant for two out of the four variables (dangerous-angry $p = .18$, dangerous-neutral $p = .16$, safe-angry $p = .05$, and safe-neutral $p = .04$). A significant main effect of gender was found, $F(1, 142) = 4.87$, $p = .03$, $n_p^2 = .03$. Males ($M = 293.38$, $SE = 11.84$) categorized pictures significantly more quickly overall than females ($M = 326.98$, $SE = 9.58$). No significant interaction involving gender, object held (safe or dangerous) or facial expression (angry or neutral) was found for reaction times.

As for accuracy rates, Box's M was not significant, $p = .07$, while Levene's test was significant for two out of the four categories (dangerous-angry, $p = .11$, dangerous-neutral, $p = .02$, safe-angry, $p = .69$, and safe-neutral, $p < .001$). A significant main effect of gender was found, $F(1, 123) = 13.69$, $p < .001$, $n_p^2 = .10$. Males ($M = 97.61$, $SE = 0.30$) were significantly more accurate at categorizing pictures than females ($M = 96.15$, $SE = 0.25$). Also, a significant interaction of object held (dangerous or safe) and gender was found with respect to accuracy rates, $F(1, 123) = 6.96$, $p = .009$, $n_p^2 = .05$. Within males, dangerous pictures ($M = 99.07$, $SE = 0.22$) were significantly more accurately categorized than safe pictures ($M = 96.15$, $SE = 0.53$). Within females, dangerous pictures ($M = 98.53$, $SE = 0.18$) were also categorized significantly more accurately than safe pictures ($M = 93.77$, $SE = 0.44$).

Handedness

Two 2 (object held) X 2 (facial expression) repeated measures mixed ANOVAs analyzed the effects of handedness on reaction times and accuracy rates. When investigating reaction times and handedness, Box's M was not significant, $p = .78$ and Levene's test of equality of error variances was not significant for all four reaction time types (dangerous angry, $p = .45$, dangerous-neutral, $p = .34$, safe-angry, $p = .46$, and safe-neutral, $p = .26$). No significant main effect of handedness was found, $F(2, 141) = 1.26$, $p = .29$, $n_p^2 = .02$, and no significant interaction was found with respect to handedness and reaction times, $F(6, 423) = 0.71$, $p = .64$, $n_p^2 = .01$. Therefore, right-handed, left-handed, and ambidextrous individuals had similar reaction times (for each type of reaction time).

With respect to accuracy rates and handedness, Box's M was significant, $p = .01$ and Levene's test of equality of error variances was not significant for all except one category (dangerous angry, $p = .34$, dangerous-neutral, $p = .004$, safe-angry, $p = .18$, and safe-neutral, p = .34). No significant main effect for handedness was found, $F(2, 122) = 0.61$, p = .54, n_p^2 = .01. Likewise, no significant interaction effects were found with regards to handedness, object held (dangerous or safe), or facial expression (angry or neutral) with respect to accuracy rates. In other words, right-handed, left-handed, and ambidextrous participants all had similar accuracy rates. Therefore, the variable handedness will not be used in further analyses.

Vision

Two, 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) were conducted to investigate whether participants who reported poor vision differed from those who reported corrected or perfect (20/20) vision on reaction time scores and accuracy rates. When investigating vision and reaction times, Box's M was significant, p = .01 and Levene's test of equality of error variances was not significant for two out of the four reaction time types (safe-angry p = .08, safe-neutral p = .26, dangerous-angry p = .05, and dangerous-neutral p = .02). No significant main effects were found for vision, $F(2, 141) = 1.31$, p = .27, n_p^2 = .02. Also, no interactions of vision, object held, or facial expression with respect to reaction times were found. Therefore, participants who reported problems with their vision, had perfect vision, or corrected vision, did not differ on their reaction times for any of the categories (dangerous-angry, dangerous-neutral, safe-angry, or safe-neutral).

As for vision and accuracy rates, Box's M was not significant, p = .13 and Levene's test of equality of error variances was not significant for all four categories (dangerous angry p = .79, dangerous-neutral p = .58, safe-angry p = .83, safe-neutral p = .39). No significant main effects were found for vision, $F(2, 122) = 0.15$, p = .86, n_p^2 = .002. Likewise, no significant interactions were found for vision, object held, or facial expression by accuracy rates. In other words, participants who reported perfect vision, corrected vision, or poor vision did not differ on their accuracy rates in any of the four types. Therefore, because no significant main effects or interactions were found regarding the variable vision, it was dropped from further analyses.

Age Range

Two, 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) were conducted to investigate age range on reaction time scores and accuracy rates. As for age and reaction times Levene's test was not significant for any of the four reaction time types (dangerous-angry p = .37, dangerous-neutral p = .24, safe-angry p = .35, and safe-neutral p = .25). No significant main effect was found for age range, $F(3, 140) = 2.08$, $p = .11$, $n_p^2 = .04$. No significant interaction effects were found for age range, object held (dangerous or safe), or facial expression (angry or neutral) with respect to reaction times. This shows that there were no differences between reported age range and reaction times for each of the categories.

As for age range with respect to accuracy rates, Levene's test was significant for two out of four accuracy rates (safe-neutral p = .02, safe-angry p = .08, dangerous-neutral p = .11, and dangerous-angry p = .002). No significant main effect was found for age range, $F(3, 121) = 0.11$, $p = .95$, $n_p^2 = .003$. Likewise, no significant interaction effects were found for age range, object held, or facial expression with respect to accuracy rates. This means that there were no differences in accuracy rates for different ages of participants. Therefore, because no significant interactions were found regarding age range, this variable was dropped from further analyses.

First Person Shooter Game

Two, 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) were conducted to investigate differences in play time for first person shooter games with respect to reaction times and accuracy rates. When investigating amount of shooter game playing time with respect to reaction times, Box's M was not significant, $p = .06$ and Levene's test was not significant for any of the four types (dangerous-angry $p = .43$, dangerous-neutral $p = .33$, safe-angry $p = .48$, and safe-neutral $p = .60$). A significant difference was found across the levels of video game playing: reported not playing video games ($M = 329.14$, $SE = 8.88$), less than one hour per day of play time ($M = 262.05$, $SE = 17.30$), one hour of video games ($M = 306.31$, $SE = 26.08$), two hours ($M = 334.57$, $SE = 30.58$), three hours ($M = 276.88$, $SE = 49.94$), four hours ($M = 377.28$, $SE = 86.50$), and more than eight hours of play time ($M = 96.56$, $SE = 86.50$), $F(6, 137) = 3.31$, $p = .004$, $n_p^2 = .13$. Participants who reported playing first person shooter games for less than one hour a day had significantly lower mean reaction times overall than those who reported not playing video games, ($p = .02$). No significant interaction effects were found for amount of first-person shooter game playing, object held, or facial expression with respect to reaction times. Therefore, overall, participants who played first-person shooter games for less than one hour a day were quicker at categorizing pictures regardless of the type.

As for first person shooter video game playing and accuracy rates, Box's M was significant, $p = .05$ and Levene's test was significant for three out of the four accuracy rate types (dangerous-angry $p = .01$, dangerous-neutral $p < .001$, safe-neutral $p = .001$, and safe-angry $p = .34$). No significant main effect was found for first person shooter video game playing time, $F(6, 118) = 1.17$, $p = .33$, $n_p^2 = .06$. Also, no significant interaction effects were found for video game playing, object held, or facial expression with respect to accuracy rates. Thus, different amounts of video game playing did not exhibit different accuracy rates on the four types of pictures (dangerous-angry, dangerous-neutral, safe-angry, safe-neutral). Therefore, amount of first-person shooter game playing as a variable was dropped from subsequent analyses.

Anxiety Scores

Two, 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) were conducted to investigate differences in anxiety with respect to reaction times and accuracy rates. When looking at reaction times and anxiety levels, Box's M was not significant, $p = .41$ nor was Levene's test, (dangerous-angry $p = .27$, dangerous-neutral $p = .59$, safe-angry $p = .66$, and safe-neutral, $p = .87$). There was no main effect of participant's level of anxiety, $F(3, 140) = 0.92$, $p = .43$, $n_p^2 = .02$. Furthermore, no significant interaction effects of anxiety level, object held, or facial expression by reaction times were detected. This indicated that regardless of the participant's anxiety type (mild, moderate, moderately severe, or severe), none of the reaction times differed.

With respect to anxiety level and accuracy rate, Box's M was not significant, $p = .07$, while Levene's test was, for two out of four categories (dangerous-angry $p = .05$, dangerous-neutral $p = .09$, safe-angry $p = .25$, and safe-neutral $p = .02$). Main effects of anxiety levels were not found, $F(3, 121) = 2.10$, $p = .10$, $n_p^2 = .05$. Furthermore, no interaction effects of anxiety, object held, or facial expression by accuracy rate were found. In essence, participant's accuracy rates did not depend on their anxiety levels. Therefore, because no main effect or interaction for anxiety levels were found, the variable GAD score was dropped from further analyses.

Military Service

Two, 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) were conducted to evaluate whether military service would play a role in reaction times and accuracy rates for the categorization game. As for military service with respect to reaction times, Levene's test was not significant for all four reaction time types (dangerous-angry $p = .10$, dangerous-neutral $p = .08$, safe-angry $p =$

.07, and safe-neutral p = .09). No significant main effect for military was found, $F(1, 142) = 0.03$, p = .87, $n_p^2 < .001$. Likewise, no significant interactions for military service, object held, or facial expression by reaction time were found. Thus, participants with military experience did not have different reaction times than those with no military experience.

As for military service by accuracy rate, Levene's test was significant for only one of the four types (dangerous-angry p = .58, dangerous-neutral p = .01, safe-angry p = .92, and safe-neutral p = .10). No significant main effect was found for military service, $F(1, 123) = 1.67$, p = .20, n_p^2 = .01. Furthermore, no significant interactions were found for military service, object held, or facial expression by accuracy rate. Thus, participants with military experience did not have different accuracy rates than those with no military experience. Therefore, the variable military service was not used in subsequent analyses.

Maximization Inventory

Reaction Times with Satisficing, Decision Difficulty, and Alternative Search Scores

A 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) was conducted to investigate whether reaction times would differ with respect to high and low scores on satisficing, decision difficulty, and alternative search. Box's M was not significant, p = .18 and equality of error variances was found for the dependent variables (dangerous-angry p = .33, dangerous-neutral p = .19, safe-angry p = .38, and safe-neutral p = .21). No main effects for the Maximizing Inventory subscale scores were found: satisficing $F(1, 136) = 0.17$, p = .68, n_p^2 =.001, decision difficulty $F(1, 136) = 0.37$, p = .54, n_p^2 = .003, or alternative search $F(1, 136) = 2.33$, p = .13, n_p^2 =.02. Likewise, no interaction effects between the subscale scores, object held, or facial expressions with respect to reaction times were found.

Accuracy Rates with Satisficing, Decision Difficulty, and Alternative Search Scores

A 2 (object held) X 2 (facial expression) repeated measures mixed analyses of variance (ANOVAs) was conducted to investigate whether accuracy rates would differ with respect to high and low scores on satisficing, decision difficulty, and alternative search. The assumption of equality of covariances (Box's M) was met, p = .47. Also, Levene's test was not significant for any of the variables (dangerous-angry p = .09, dangerous-neutral p = .78, safe-angry p = 1.00, and safe-neutral p = .75). No main effects for the Maximizing Inventory subscale scores were found: satisficing $F(1, 117)$ = 0.13, p = .72, n_p^2 =.001, decision difficulty $F(1, 117)$ = 0.58, p = .45, n_p^2 = .005, or alternative search $F(1, 117)$ = 0.12, p = .73, n_p^2 = .001. Likewise, no interaction effects between the subscale scores, object held, or facial expression with respect to accuracy rates were found. Therefore, since no differences were found between satisficing, decision difficulty, and alternative search scores with respect to reaction times and accuracy rates, the variable maximization was dropped from further analyses and not mentioned again.

Racial Bias

One bivariate correlation was conducted to examine if the covariates (overall racial bias, African American racial bias, and Middle Eastern racial bias) were in fact related to the dependent variables reaction times and accuracy rates. For overall racial bias, the four reaction times, and the four accuracy rates, only one significant correlation was found with the variable safe-angry accuracy rate and overall racial bias, $r(136)$ = -.23, p = .007. Therefore, using overall racial bias as a covariate in further analyses is not warranted and the variable will not be mentioned again.

The correlation between the accuracy rates, the reaction times, and African American racial bias revealed no significance for any of the pairings and so the variable was dropped.

Lastly, an investigation of the correlations between Middle Eastern racial bias, reaction times, and accuracy rates revealed no significant correlations. Therefore, Middle Eastern racial bias as a covariate was not warranted and was dropped from further analyses.

Hypotheses

Reaction Times

To assess for main effects of reaction times, a 2 (object held—dangerous/safe) X 2 (facial expression—angry/neutral) factorial repeated measures analysis of variance (ANOVA) was conducted. For dangerous versus safe reaction times, a significant overall effect was found, $F(1, 143) = 6.09$, $p = .02$, $n_p^2 = .04$. As expected, participants categorized dangerous pictures significantly more quickly ($M = 310.90$, $SE = 7.60$) than safe pictures ($M = 316.46$, $SE = 7.66$). See Figure 3-1 for representation of the main effect of object held (dangerous versus safe reaction times). With regards to comparing reaction times of pictures with angry or neutral facial expressions, no significant effect was found ($p = .23$), which was contrary to expectations. Participants categorized angry ($M = 312.60$, $SE = 7.49$) and neutral ($M = 314.76$, $SE = 7.71$) pictures roughly at the same speed.

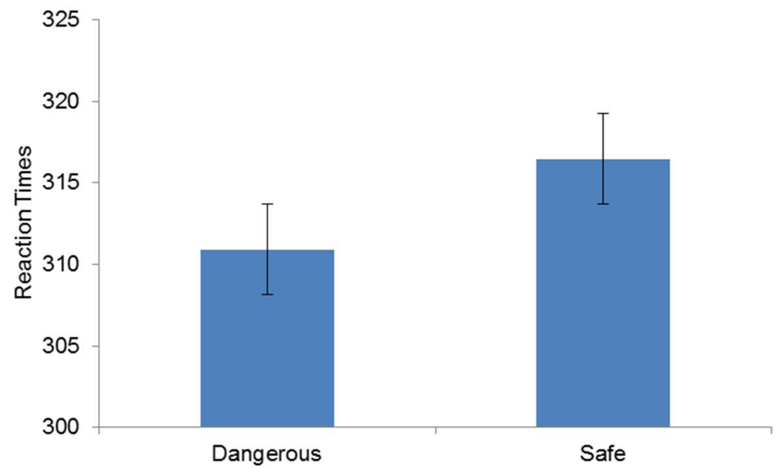


Figure 3-1 Main Effects of Dangerous and Safe Reaction Times

As expected, a significant interaction effect of object held on facial expression was found with respect to reaction times, $F(1, 143) = 7.87$, $p = .006$, $n_p^2 = .05$. Within the dangerous pictures, angry pictures ($M = 307.18$, $SE = 7.34$) were categorized significantly more quickly than neutral ($M = 314.63$, $SE = 8.09$), ($p = .007$) pictures. Contrary to expectations, within the safe pictures, angry reaction times ($M = 318.03$, $SE = 7.89$) did not differ significantly from neutral reaction times ($M = 314.89$, $SE = 7.64$) ($p = .21$). As expected, the difference between safe-angry and safe-neutral mean reaction times ($M = 3.14$) was smaller than the difference between dangerous-angry and dangerous neutral mean reaction times ($M = 7.46$). As expected, within the pictures that had angry facial expressions, dangerous pictures (holding weapons) were categorized significantly more quickly than safe (holding innocuous items), ($p < .001$). Contrary to expectations, within the neutral pictures, dangerous and safe were categorized roughly at the same speed ($p = .93$). Refer to Figure 3-2 for the interaction effects.

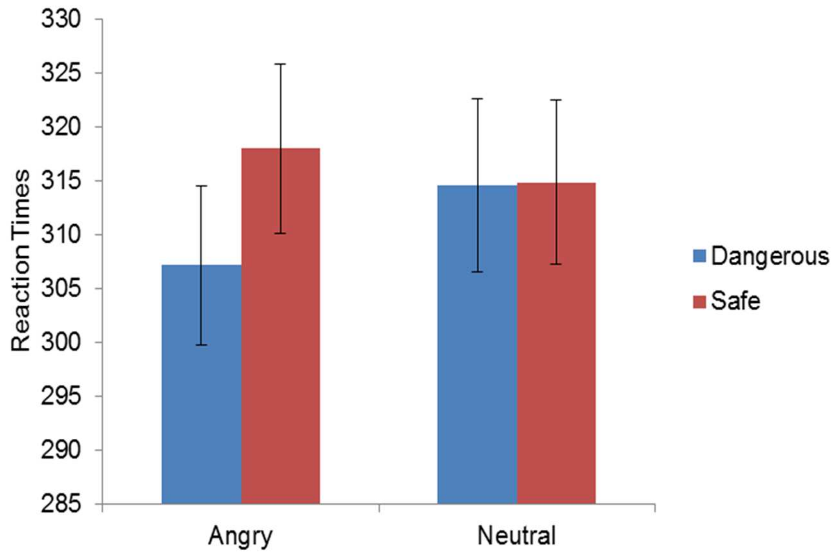


Figure 3-2 Interaction Effects of Picture Category with Reaction Times

Accuracy Rates

A 2 (object held – dangerous, safe) X 2 (facial expression – angry, neutral) factorial repeated measures ANOVA was conducted with the dependent variables accuracy rates. As expected, a main effect of object held was found with respect to accuracy rates, $F(1, 124) = 130.51$, $p < .001$, $n_p^2 = .51$. Dangerous pictures (weapons held) ($M = 98.75$, $SE = 0.14$) were categorized significantly more accurately than safe pictures (innocuous items held) ($M = 94.74$, $SE = 0.35$). Refer to Figure 3-3 for illustration of the main effects of object held (dangerous and safe pictures) on accuracy rates.

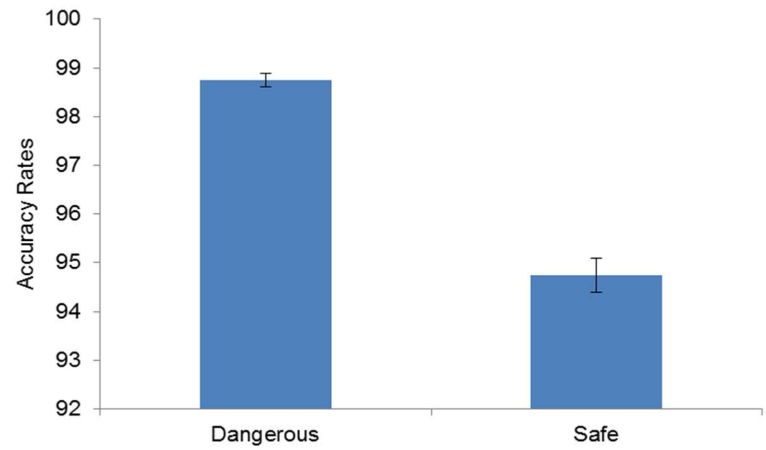


Figure 3-3 Main Effects of Dangerous and Safe Accuracy Rates

Also as expected, analyses revealed a main effect of facial expression with respect to accuracy rates, $F(1, 124) = 25.25$, $p < .001$, $n_p^2 = .17$. Pictures of people with neutral facial expressions ($M = 97.42$, $SE = 0.23$) were categorized significantly more accurately than pictures of people with angry facial expressions ($M = 96.07$, $SE = 0.26$). Refer to Figure 3-4 for illustration of the main effect of facial expression on accuracy rates.

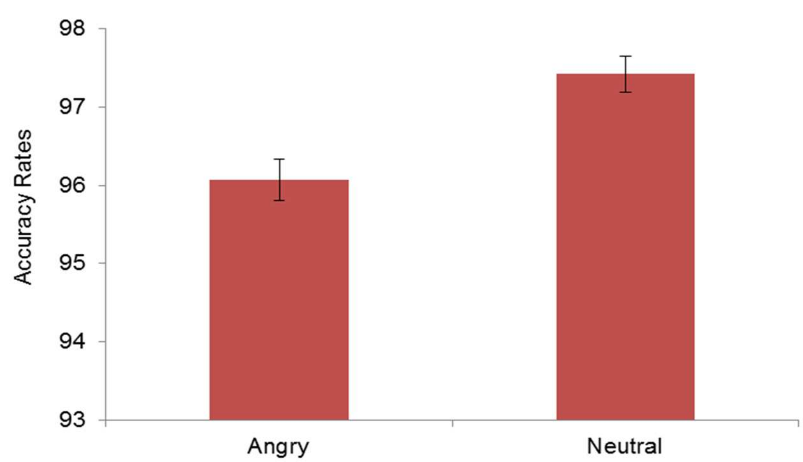


Figure 3-4 Main Effects of Angry and Neutral Accuracy Rates

Furthermore, a significant interaction between object held and facial expression was found with respect to accuracy rates, $F(1, 124) = 25.96$, $p < .001$, $n_p^2 = .17$, which was expected. However, contrary to expectations, within dangerous pictures, angry (M = 98.74, SE = 0.18) and neutral (M = 98.77, SE = 0.19) accuracy rates were approximately the same (p = .89). As expected, within safe pictures, neutral pictures (M = 96.08, SE = 0.40) were categorized much more accurately than angry pictures (M = 93.40, SE = 0.45) (p < .001). As expected, within angry pictures, dangerous were categorized significantly more accurately than safe pictures (p < .001). Also as expected, within neutral pictures, dangerous were categorized significantly more accurately than safe (p < .001). Refer to Figure 3-5 for illustration of the interaction of object held by facial expression on accuracy rates.

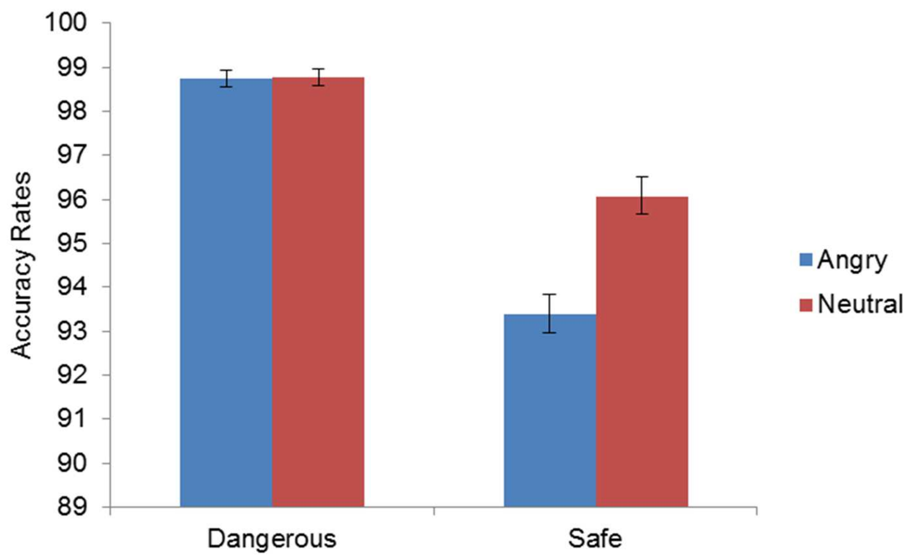


Figure 3-5 Interaction Effects of Picture Category on Accuracy Rates

Chapter 4

Discussion

Hypotheses

The purpose of this experiment was to investigate the role of facial expressions in categorizing threatening versus non-threatening images under time pressure to understand if the neural hypothesis involving the amygdala, orbitofrontal cortex, and the anterior cingulate cortex was supported. Many studies have involved the investigation of racial bias with facial expressions and danger (Correll, 2005; Kubota & Ito, 2014), racial bias and danger (Kenworthy et al., 2011, Correll et al. 2014; Peruche & Plant, 2006), and facial expression and attention (Lassalle & Itier, 2013; Neath, Nilsen, Gittsovich, & Itier, 2013, Rigato, Memon, Di Gangi, George, & Farroni, 2013; Williams, McGlone, Abbot, and Mattingley, 2004). However, no other research has yet investigated just the influence of facial expressions on the categorization of threatening situations.

Some support was lent to the hypothesis that the amygdala and OFC work together to categorize emotional stimuli more quickly and accurately than non-emotional stimuli. As expected, participants categorized pictures with weapons (dangerous) faster than pictures with innocuous items (safe). Furthermore, as expected, dangerous pictures (weapons) were categorized more accurately than safe (innocuous items) pictures. Also as expected, within pictures showing people with angry facial expressions, dangerous pictures were categorized much more quickly than safe pictures. Likewise, within dangerous pictures (pictures with people holding weapons), angry were categorized more quickly than neutral. Moreover, within pictures showing people with angry facial expressions, dangerous pictures were categorized more accurately than safe. These previous findings lent support to the idea that dangerous-angry pictures were the most emotional while safe-angry pictures were less emotional and therefore categorized less quickly, which reiterates past research findings that threatening pictures are recognized more quickly than positive pictures (Genschow, Florack, & Wanke, 2013).

However, contrary to the hypothesis, pictures showing people with neutral facial expressions were more accurately categorized than pictures showing people with angry facial expressions. Also, pictures that included people with angry facial expressions were not categorized more quickly than pictures with people showing neutral facial expressions. Angry and neutral pictures were categorized roughly at the same pace, which was opposite of what was expected. Furthermore, within the neutral pictures, participants categorized dangerous pictures (weapons) in roughly the same amount of time as safe (innocuous items). These results might be due to the fact that the overall angry category included dangerous-angry and safe-angry pictures while the overall neutral category included dangerous-neutral, and safe-neutral pictures. The safe-angry category had the most errors, thus, perhaps making the overall angry category less accurate. As for reaction times, these inclusions could possibly cancel out the effect of the tendency to react quickly to angry facial expressions, thus, showing an overall preference to react quickly to threatening stimuli regardless of facial expression. However, an alternative explanation may exist. Past research indicates that when a neutral facial expression is seen after angry facial expressions, it is recognized biasedly as a slightly positive facial expression instead of totally neutral (Marian & Shimamura, 2013; Jellema, Pecchinenda, Palumbo & Tan, 2011). Furthermore, past research has shown an attentional bias towards happy facial expressions which are chosen from a crowd faster than angry faces (Dodd & Porter, 2010; Becker, Anderson, Mortensen, Neufeld, & Neel, 2011). This may be cancelling out the natural tendency to react more quickly to angry facial expressions.

The next hypothesis explained that the anterior cingulate cortex identifies conflicting information during the categorization process, thus slowing down decision making for non-congruent pictures (dangerous-neutral and safe-angry). This hypothesis was partially supported. Participants categorized pictures involving people with angry facial expressions holding weapons (dangerous-angry) more quickly and accurately than pictures involving people with angry facial expressions holding innocuous items (safe-angry), lending credence to the theory that the ACC slows down decision making when conflicting information is encountered. Furthermore, pictures of people with angry facial expressions holding weapons (dangerous-angry) were categorized more quickly than pictures of people with neutral facial expressions holding weapons (dangerous-neutral). Since dangerous-neutral is more conflicting than dangerous-angry pictures, longer reaction times were required to make a decision for participants. Also, the difference between safe-angry and safe-neutral mean reaction times was smaller than the difference between dangerous-angry and dangerous-neutral mean reaction times. Interestingly, safe-angry pictures were the least accurately categorized out of all of the types of pictures, thus supporting the idea that safe-angry pictures involved the most conflict thus requiring the longest amount of time to categorize. All of these results echo past research findings where reaction times were slower for participants implicitly viewing incongruent scenes (Mudrik & Kock, 2013) and for participants viewing stroop-type stimuli which are incongruent (Head & Tunstall, 1990).

However, contrary to the hypothesis, within the neutral pictures, participants categorized dangerous pictures (weapons) in roughly the same amount of time as safe (innocuous items). This could possibly be due to the ambiguous nature of neutral facial expressions (Blasi, Hariri, Alce, Taruisano, Sambataro, Das, Bertolino, Weinberger, & Venkata, 2009). If participants are viewing neutral facial expressions and interpreting them in other ways besides being neutral, this could affect how quickly the pictures are categorized.

Also, within the pictures which had people with neutral facial expressions, dangerous (holding weapons) were categorized more accurately than safe (holding innocuous items) which was opposite of what was expected. Within dangerous pictures, angry was categorized as accurately as neutral pictures. Both of these are probably due to the main effect of dangerous pictures. Threatening stimuli were categorized more accurately overall, regardless of facial expression.

Furthermore, pictures of people with angry facial expressions holding innocuous items (safe-angry) did not differ in reaction time from pictures of people with neutral facial expressions holding innocuous items (safe-neutral). In other words, within the safe pictures, angry facial expressions and neutral facial expressions were categorized at roughly the same speed. Recall that the safe-angry category was least accurately categorized overall. Perhaps participants were maintaining their speed of categorization at the expense of their accuracy. This reiterates past research findings of the speed-accuracy trade off in which accuracy is given up for quickness of decision-making (Donkin, Little & Houpt, 2014).

Some explanation of the partial support of the hypotheses might be due to the pictures themselves. All of the pictures were chosen from Google Images. The backgrounds of the pictures were all different which represented real life but also introduced some error into the reaction times and accuracy rates. The pictures were rated by laboratory assistants, on all categories: dangerousness, safeness, angriness, and neutrality to remove the photos that were not representative, before participants played the game. This attempted to cut down on some of that error due to the pictures' differences. This may explain why there were some small and medium effect sizes.

Perhaps if they were all uniform in background with precise facial expressions the effect sizes could have been larger.

Each of the hypotheses was half supported, suggesting that there might be relevance to the theory that the amygdala codes emotional information into memory while the OFC correctly categorizes the emotional information, and the ACC slows down decision making in the event of conflicting information to categorize correctly. In support of this idea, dangerous pictures were found to be categorized the quickest and the most accurately overall while dangerous-angry pictures (the most emotional) were also categorized much more quickly than less emotional pictures. Furthermore, the most conflicting pictures (safe-angry and dangerous-neutral) took the longest for participants to categorize. This suggests that there may be an actor-critic structure at work here with the amygdala and OFC as the actor, and the ACC as the critic. In other words, the actor (amygdala and OFC) is like an impulsive teenager driven by emotion, categorizing quickly without much regard to correctness, but with much regard to quickness. The ACC however, is like an older, wiser parent who checks the teens' work slowly for preciseness, and corrects the teen when he or she is wrong. This means that there may be some credence to using Levine's 2012 neural network model as a stepping stone for engineers to solve their mathematical reinforcement learning problems.

However, as stated earlier, 4.6% of the participants chose not to participate in the game but filled out the surveys. When comparing the 4.6% to the others on scores of the Maximization Inventory, the participants differed. Those who chose not to play the categorization game had much lower satisficing scores, indicating a non- willingness to accept a solution as "satisfactory". Also, those who opted not to play the game had much lower alternative search scores than did those who played the game. This showed that those who chose not to play took much less time to make a decision because they did not search for alternative answers, unlike the group who chose to play the game. Perhaps the differences in these scores could be due to the need to resolve cognitive dissonance for those who made the decision not to play. Cognitive dissonance is the mental discomfort one feels when one of their actions does not match up with one or more of their beliefs, or values. For example, if someone says they are not a thief but then steals a candy bar, this would create mental discomfort or cognitive dissonance. Cognitive dissonance is resolved by changing the thought or the behavior, justifying the thought or behavior, or ignoring the thought or behavior (Festinger, 1962). Therefore, if participants made the decision to not participate in some of the experiment, this would contradict their actions and beliefs when they signed up for the experiment and agreed to participate in it, thus, causing some cognitive dissonance. So, in order to resolve the dissonance, it is possible that the participants justified their thought process with something like, “I agreed to participate, but I did not specify to how much I would participate”. This, itself is a satisfactory answer which may have primed participants into having lower satisficing scores. Furthermore, it is possible that in order to resolve dissonance further, participants ignored any other discomforting thought, thus reaching their answer and sticking to it. This could have led to lower alternative search scores. Whatever the case or explanation, the final sample had overall higher satisficing scores and alternative search scores which limited the generalizability of the results to those who are also slightly higher on alternative search and satisficing scores.

Importance of Research

There are a couple of reasons why this work was important, the first and foremost was to investigate whether there was a possible actor-critic structure with respect to the amygdala, OFC, and ACC. This knowledge allows engineers to take this neural network and use it to solve future reinforcement learning problems via adaptive dynamic programming. What this means is: better robots for tomorrow.

Secondly, there have been a tremendous number of shootings of unarmed civilians by cops in the news lately. Other research shows that race plays a significant role in making shoot decisions, however, it was important to investigate what role emotional expression played in the categorization of dangerous and safe situations. As for this aspect, facial expressions do affect how the situation is perceived; pictures with safe people holding no weapons who expressed anger were the least accurately categorized, meaning that they were often deemed "dangerous" and having weapons when they indeed did not.

In real life, this could mean the difference between life and death. If people are willing to unjustly categorize someone as being dangerous if they are angry, even when there is no sign of a weapon, then people could also be willing to shoot someone unjustly who looks angry even if that person is not holding a weapon. This may indicate that a neutral expression or, better yet, a smile, may save a life.

Future Directions

As for future directions of this research, first, it would be beneficial to make the pictures more uniform by having the same backgrounds to see if that clears up some of the contradictory findings with angry and neutral pictures. It might also be beneficial to compare happy facial expressions with angry facial expressions with respect to safe and dangerous situations. This would allow for a cleaning up of the ambiguous neutral faces which can be interpreted as either happy, angry, or neutral. Also, it would be very interesting to change the paradigm in the future to the "shoot, no shoot" style of experiment while adding smiling faces. It would be beneficial to see if a smile would lead to better decisions regarding safe people. These changes might elucidate some answers to the discrepancies found in this research.

Appendix A

Self-Report Measures

Demographic Survey
1. What is your gender:
A. Male
B. Female
2. Have you ever served in the military?
A. Yes
B. No
3. What is your ethnicity:
A. African-American, Black
B. Chinese
C. Filipino
D. Indian
E. Japanese
F. Korean
G. Southeast Asian
H. White Caucasian – Non Hispanic
I. Hispanic or Latino
J. Mexican
K. American Indian, Alaskan Native
L. Middle Eastern
M. More than one race
4. Are you right handed, left handed or ambidextrous?
A. Left-handed
B. Right-handed
C. Ambidextrous
5. Indicate the state of your vision:
A. 20/20 uncorrected vision
B. Corrected with glasses or contact lenses
C. Problems with vision
6. What is your age range:
A. 18-28
B. 29-38
C. 39-48
D. 49-58
E. 59-68
F. 69-78
G. 79 and up
7. How often do you play (on average) first person shooter video games?
A. 0 (I do not play first person shooter video games)
B. Less than 1 hour a day
C. 1 hour a day
D. 2 hours a day
E. 3 hours a day
F. 4 hours a day
G. 5 hours a day
H. 6 hours a day
I. 7 hours a day
J. 8 hours a day
K. More than 8 hours a day

Generalized Anxiety Disorder

(Spitzer, Williams, & Kroenke, 1995)

Directions: Over the last 2 weeks, how often have you been bothered by the following problems?

Scale

0 = Not at all
1 = Several days
2 = More than half the days
3 = Nearly every day

1. Feeling nervous, anxious or on edge
2. Not being able to stop or control worrying
3. Worrying too much about different things
4. Trouble relaxing
5. Being so restless that it's hard to sit still
6. Becoming easily annoyed or irritable
7. Feeling afraid, as if something awful might happen

Maximization Inventory

(Turner, Rim, Betz, & Nygren, 2012)

Directions: Please select the answer that best fits you.

Scale

1 = Strongly Disagree
2 = Disagree
3 = Somewhat Disagree
4 = Somewhat Agree
5 = Agree
6 = Strongly Agree

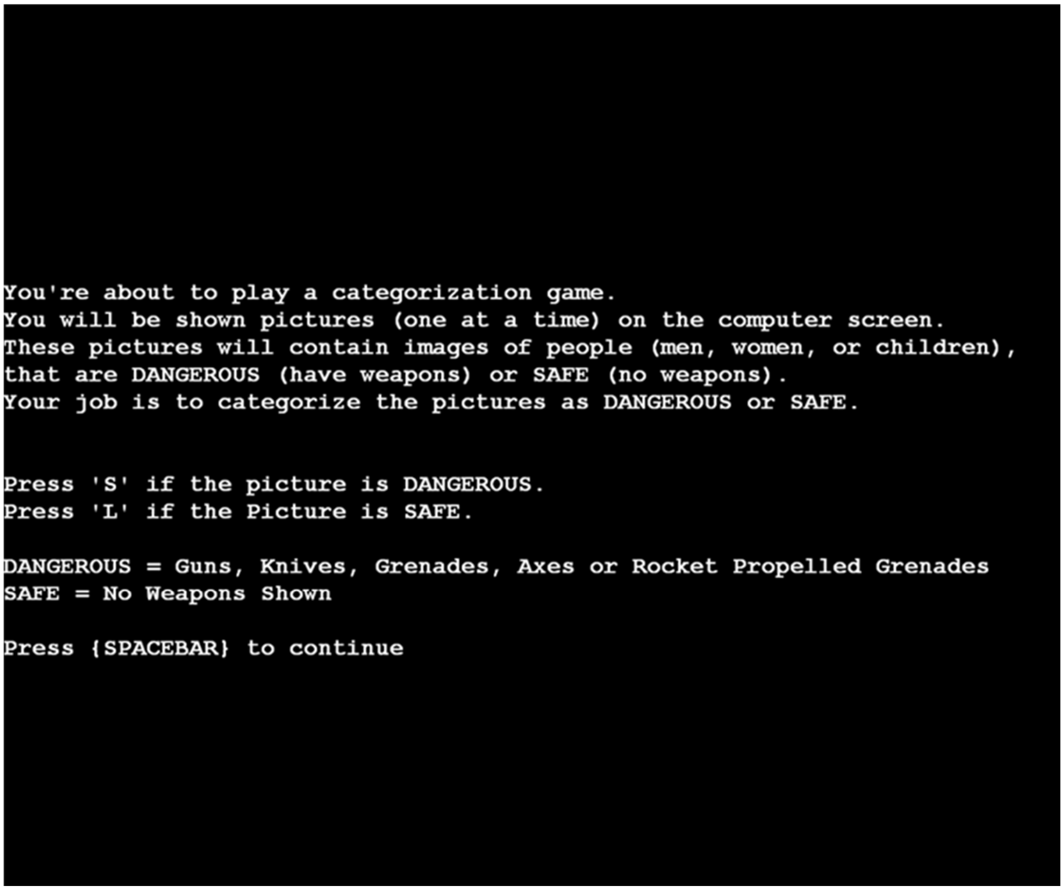
1. I usually try to find a couple of good options and then choose between them.
2. At some point you need to make a decision about things.
3. In life I try to make the most of whatever path I take.
4. There are usually several good options in a decision situation.
5. I try to gain plenty of information before I make a decision, but then I go ahead and make it.
6. Good things can happen even when things don't go right at first.
7. I can't possibly know everything before making a decision.
8. All decisions have pros and cons.
9. I know that if I make a mistake in a decision that I can go "back to the drawing board."
10. I accept that life often has uncertainty.
11. I usually have a hard time making even simple decisions.
12. I am usually worried about making a wrong decision.
13. I often wonder why decisions can't be more easy.
14. I often put off making a difficult decision until a deadline.
15. I often experience buyer's remorse.
16. I often think about changing my mind after I have already made my decision.
17. The hardest part of making a decision is knowing I will have to leave the item I didn't choose behind.
18. I often change my mind several times before making a decision.
19. It's hard for me to choose between two good alternatives.
20. Sometimes I procrastinate in deciding even if I have a good idea of what decision I will make.
21. I find myself often faced with difficult decisions.
22. I do not agonize over decisions.
23. I can't come to a decision unless I have carefully considered all of my options.
24. I take time to read the whole menu when dining out.
25. I will continue shopping for an item until it reaches all of my criteria.
26. I usually continue to search for an item until it reaches my expectations.
27. When shopping, I plan on spending a lot of time looking for something.
28. When shopping, if I can't find exactly what I'm looking for, I will continue to search for it.
29. I find myself going to many different stores before finding the thing I want.

30. When shopping for something, I don’t mind spending several hours looking for it.
31. I take the time to consider all alternatives before making a decision.
32. When I see something that I want, I always try to find the best deal before purchasing it.
33. If a store doesn’t have exactly what I’m shopping for, then I will go somewhere else.
34. I just won’t make a decision until I am comfortable with the process

Appendix B

The Experiment

Instructions



Pictures Used

DAas100.bmp

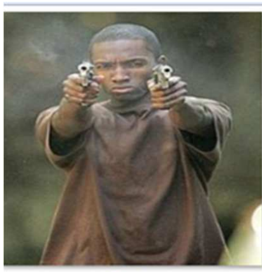
DAas101.BMP

DAas102.BMP

DAas103.BMP

DAas104.BMP

DAas105.BMP



DAB5.jpg

DAB23.jpg

DAB35.jpg

DAB43.jpg

DAB45.jpg

DAB50.jpeg


DAH6.jpg


DAH30.jpg


DAH53.jpg


DAH103.BMP


DAH105.BMP


DAH106.BMP


DAME15.jpg


DAME20.jpg


DAME31.jpg


DAME41.jpg


DAME47.jpg


DAME100.BMP


DAW3.jpg
DAW7.jpg
DAW24.jpg
DAW39.jpg
DAW48.png
DAW49.jpg

DNB26.jpg

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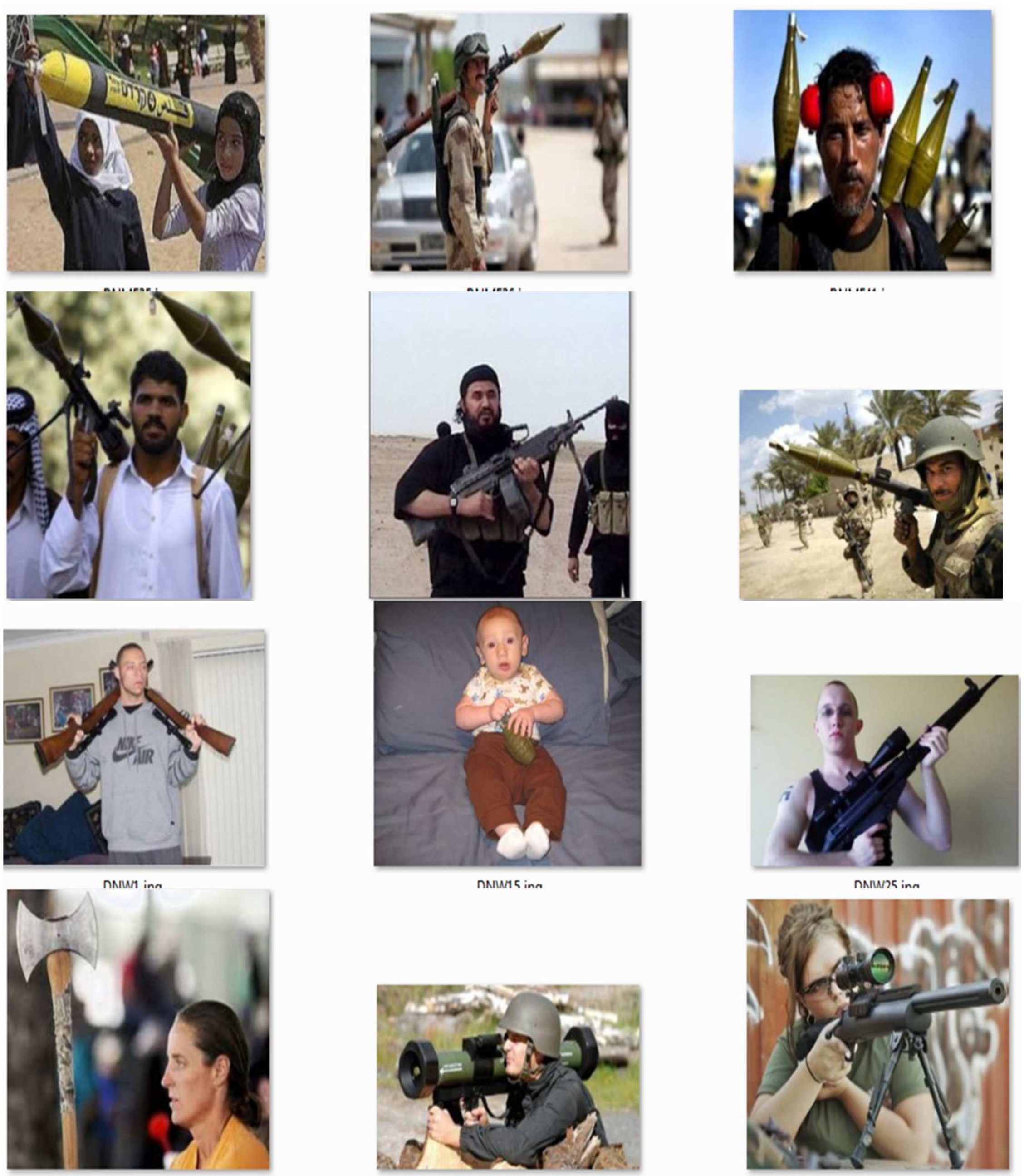
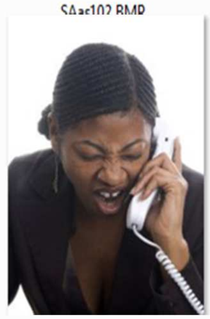


SAas101.BMP

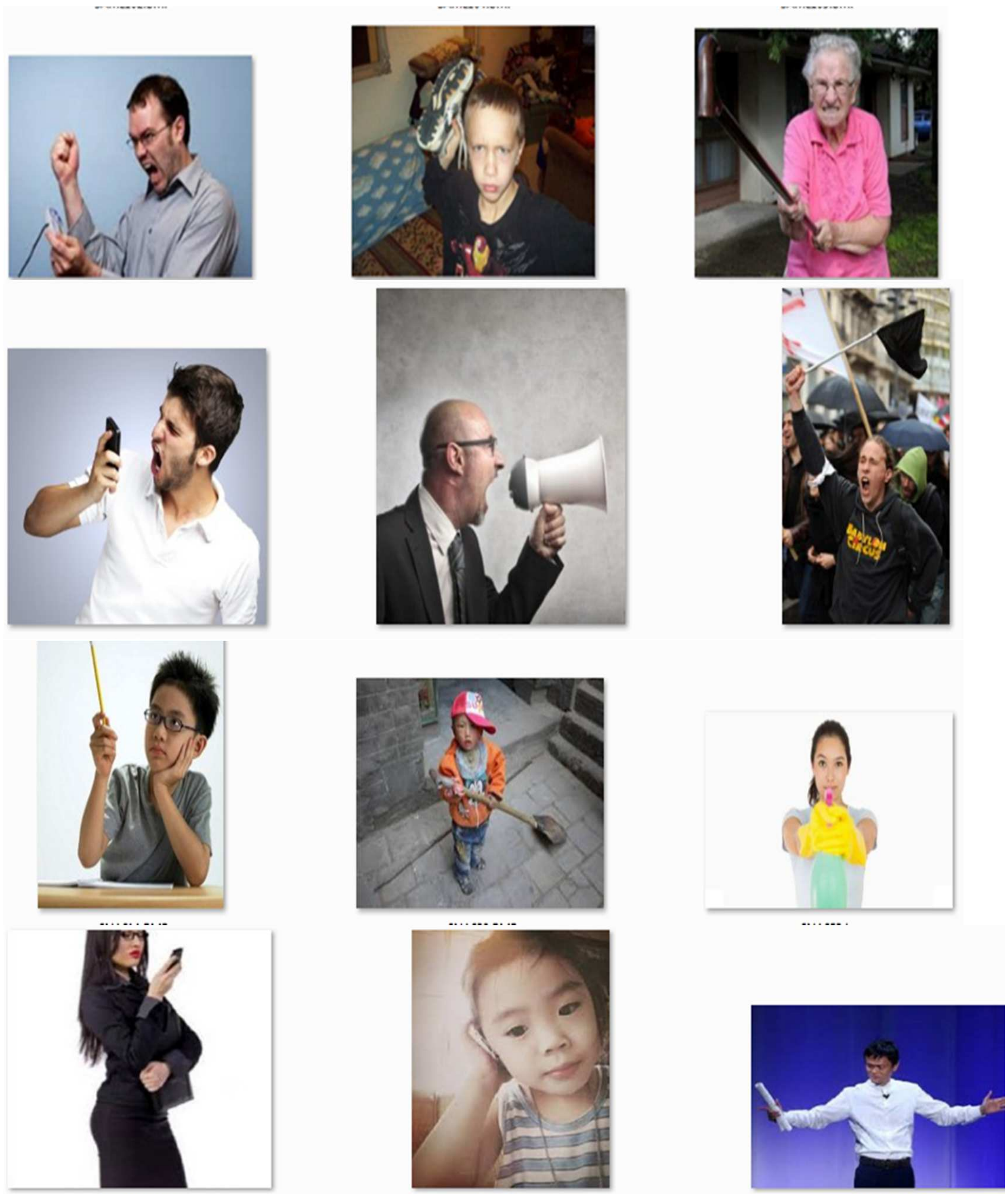
SAas102.BMP

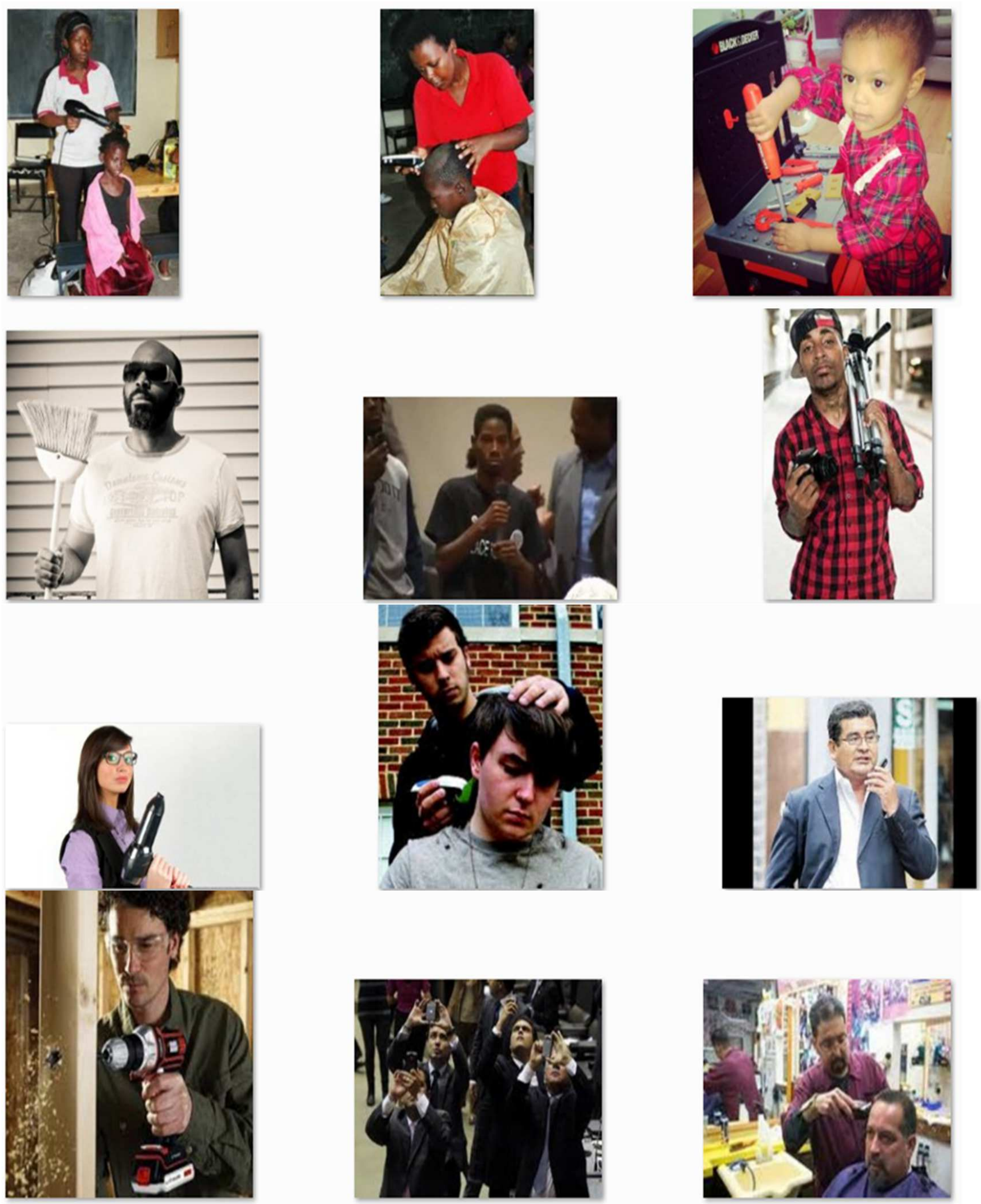
SAas103.BMP


SAME27.jpg
SAME100.BMP
SAME101.BMP







SNME103.BMP

SNME104.BMP

SNME105.BMP





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