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# What makes an object memorable?

Anonymous ICCV submission

Paper ID \*\*\*\*

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## Abstract

Recent work by Isola et. al. (2011) has demonstrated that memorability is an intrinsic property of images that is consistent across viewers and can be predicted accurately with current computer vision techniques. Despite progress, a clear understanding of the specific components of an image that drive memorability are still unknown. While previous studies such as Khosla et. al. (2012) have tried to investigate computationally the memorability of image regions within individual images, no behavioral study has systematically explored which memorability of image regions. Here we study which region from an image is memorable or forgettable. Using a large image database, we obtained the memorability scores of the different visual regions present in every image. In our task, participants viewed a series of images, each of which were displayed for 1.4 seconds. After the sequence was complete, participants similarly viewed a series of image regions and were asked to indicate whether each region was seen in the earlier sequence of full images.

## 1. Introduction

Consider the image and its corresponding objects in Figure 1. Even though the person on the right is comparable in size to the left person, he is remembered far less by humans (indicated by their memorability scores of 0.18 and 0.64 respectively). People tend to remember the fish in the center and the person on the left, even after 30 minutes have passed (memorability score = 0.64). Interestingly, despite vibrant colors and considerable size, the boat is also remembered far less by humans (memorability = 0.18).

NOTE: Big picture way to think about this (rough): A currently massive goal in computer science and artificial intelligence is to model the data driven inference processes that humans make use of for solving vision problems, such as object recognition and scene understanding. A subset of these processes make use of nearly all of the information in the scene, much of which is used implicitly but others are dependent on more explicitly remembered information in



Figure 1: Not all objects are equally remembered. Memorability scores of objects for the image in the top row obtained from our psychophysics experiment.

a scene, that is, the information that the brain has deemed worthy to create special storage for. For example, the recognition of edges in a scene is learned and used automatically, but if we ask a person to report the important information in a scene, only a few high level things are reported. More specifically, humans can only make judgements about elements of an image that they can remember...

Just like aesthetics, interestingness, and other metrics of image importance, memorability quantifies something about the utility of a photograph toward our everyday lives. For many practical tasks, memorability is an especially desirable property to maximize. For example, this may be the case when creating educational materials, logos, advertisements, book covers, websites, and much more. Understanding memorability, and being able to automatically predict it, lends itself to a wide variety of applications in each of these areas. **rewrite this to draw attention of reviewer to importance of image memorability.** Due to this, automatic prediction of intrinsic memorability of images using computer vision and machine learning techniques has received considerable attention in the recent years [5], [6], [4], [2], [7]. While these studies have shed light on what distinguishes the memorability of different images and the intrinsic and extrinsic properties that make those images memorable, the above example raises an interesting question: what exactly about an image is remembered? Despite progress in the computer vision literature on image memorability, a clear understanding of the memorability of the specific components of an image is still unknown. For example, not all objects in an image will be equally remembered by people and as the figure 1 seems to suggest, there exists significant

108 and interesting differences in memorability of objects in an  
109 image. Furthermore, the memorability of complex images  
110 may be principally driven by the memorability of its objects.  
111 Can specific objects inside images be memorable to  
112 all us and how can we better understand what makes those  
113 objects more memorable?

114 In this paper, we systematically explore the memorability  
115 of objects within individual images and shed light  
116 on the various factors and properties that drive object  
117 memorability by augmenting both the images and object  
118 segmentations in the 850 existing images from PASCAL  
119 2010 [3] dataset with memorability scores and class labels.  
120 By exploring the connection between object memorability,  
121 saliency, and image memorability, our paper makes several  
122 important contributions.

123 Firstly, we show that just like image memorability, object  
124 memorability is a property that is shared across subjects  
125 and objects remembered by one person are also likely  
126 to be remembered by others and vice versa. Secondly, we  
127 show that there exists a strong correlation between visual  
128 saliency and object memorability and demonstrate insights  
129 when can visual saliency directly predict object memorability  
130 and when does it fail to do so. While there have been  
131 have a few studies that explore the connection between image  
132 memorability and visual saliency [2], [11], our work is  
133 the first to explore the connection between object memorability  
134 and visual saliency. Third, we explore the connection  
135 between image memorability and object memorability  
136 and show that the most memorable object inside an image  
137 can be a strong predictor of image memorability in certain  
138 cases. Studying these questions, help not only understand  
139 visual saliency, image and object memorability in more detail,  
140 but it can also have important contributions to computer  
141 vision. For example, understanding which regions and objects  
142 in an image are memorable would enable us to modify  
143 the memorability of images which can have applications in  
144 advertising, user interface design etc. With this in mind,  
145 as shown in the section 4, our proposed dataset serves as  
146 a benchmark for evaluating object memorability model  
147 algorithms and can help usher in future algorithms that try to  
148 predict memorability maps.

## 149 1.1. Related works

150 **Image Memorability:** Describe Isola's first paper n  
151 some insights that have been raised on image memorability  
152 thus far. Also describe Khosla's comp model but we are  
153 the first work to actually describe what humans actually  
154 remember and don't

155 **Visual Saliency:** Talk about visual attention and models  
156 that have been proposed. Also, talk about Pascal-S and how  
157 it has helped reduce dataset bias

158 **Saliency and memorability:** discuss some results related  
159 to saliency and image memorability.

160 and talk about our work plans on connecting and shedding  
161 light on all these phenomena together.

## 162 2. Measuring Object Memorability

163 As a first step towards understanding memorability of  
164 objects, we built an image database containing a variety of  
165 objects from a diverse range of categories, and measured the  
166 probability that every object in each image will be remembered  
167 by a large group of subjects after a single viewing.  
168 This helps provide ground truth memorability scores for the  
169 objects inside the images and allows for a precise analysis  
170 of the memorable elements within an image. For this task,  
171 we utilized the PASCAL-S dataset [8], a fully segmented  
172 dataset built on the validation set of the PASCAL VOC  
173 2010 [3] segmentation challenge. For improved segmentation  
174 purposes, we manually cleaned up and refined the segmentations  
175 from this dataset. We removed all homogenous  
176 non-object or background segments such as ground, grass,  
177 floor, sky etc, as well as imperceptible object fragments and  
178 excessively blurred regions. All remaining object segmentations  
179 were tested for memorability. In the end, our final  
180 dataset consisted of 850 images and 3412 object segmentations  
181 i.e. on average each image consisted of approximately  
182 4 object segments for which we gathered the ground truth  
183 memorability on.

### 184 2.1. Memory Game: Measuring Object Memorability

185 To measure the memorability of individual objects from  
186 our dataset, we created an alternate version of the Visual  
187 Memory Game through Amazon Mechanical Turk following  
188 the basic design in [5], with the exception of a few key  
189 differences. In our game, participants first viewed a  
190 sequence of images one at a time, with a 1.5 second gap in  
191 between image presentations. Subjects were asked to remember  
192 the contents and objects inside those images as much as  
193 they could. To ensure that subjects would not just only look  
194 at the salient or center objects, subjects had unlimited time  
195 to freely view the images. Once they were done viewing an  
196 image, they could press any key to advance to the next image.  
197 Following the initial image sequence, participants then  
198 viewed a sequence of objects, their task then being to indicate  
199 through a key press which of those objects was present  
200 in one of the previously shown images. Each object was  
201 displayed for 1.5 second, with a 1.5 second gap in between  
202 the object sequences. Pairs of corresponding image and object  
203 sequences were broken up into 10 blocks. Each block  
204 consisted of 80 total stimuli (35 images and 45 objects), and  
205 lasted approximately 3 minutes. At the end of each block,  
206 the subject could take a short break. Overall, the experiment  
207 took approximately 30 minutes to complete.

208 Unknown to the subjects, inside each block, each sequence  
209 of images was pseudo-random and consisted of 3

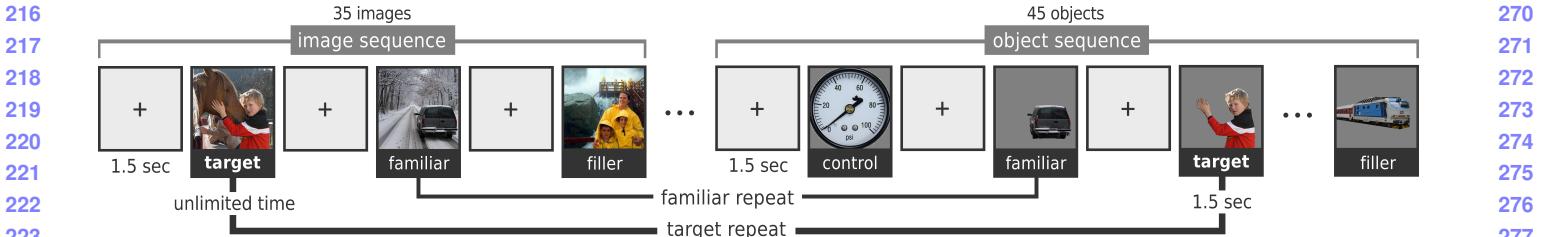


Figure 2: Main task. add-in later.

'target' images taken from the Pascal-S dataset whose objects the participants were to later identify. The remaining images in the sequence consisted of 16 'filler' images and 16 'familiar' images. The 'filler' images were randomly selected from the DUT-OMRON dataset [12] and the 'familiar' images were randomly sampled from the MSRA dataset proposed in [10]. Similarly, the object sequence was also pseudo-random and consisted of 3 'target' objects (1 object taken randomly from each previously shown target image). The remaining objects in the sequence consisted of 10 'control' objects, 16 'filler' objects, and 16 'familiar' objects. The 'filler' objects were taken randomly from the 80 different object categories in the Microsoft COCO dataset [9] and the 'familiar' objects were the objects taken from the previously displayed 'familiar' images in the image sequence. The fillers and familiars helped provide spacing between the target images and target objects, whereas the control objects allowed us to check if the subjects were paying attention to the task [1], [5]. While the fillers and familiars (both the images and objects) were taken from datasets resembling real world scenes and objects, the 'control' objects were artificial stimuli randomly sampled from the dataset proposed in [1] and helped serve as a control to test the attentiveness of the subjects. The target images and the respective target objects were spaced 70 – 79 stimuli apart, and familiar images and their respective objects were spaced 1 – 79 stimuli apart. All images and objects appeared only once, and each subject was tested on only one object from each target image. Objects were centered within their parent frame and non-object pixels were set to grey. Participants were required to complete the entire task, which included 10 blocks (overall time approximately 30 minutes), and could not participate in the experiment a second time. After collecting the data, we assigned a 'memorability score' to each target object in our dataset, defined as the percentage of correct detections by subjects. In all our analysis, we removed all subjects whose accuracy on the control objects was below 70%. In the end, our analysis was performed on a total of 1823 workers from Mechanical Turk ( $> 95\%$  approval rate in Amazons system). On average, each object was scored by 16 subjects and the average memorability score was 33% ( $SD = 28\%$ ).

## 2.2. Consistency Analysis

To assess human consistency in remembering objects, we repeatedly divided our entire subject pool into two equal halves and quantified the degree to which memorability scores for the two sets of subjects were in agreement using Spearman's rank correlation ( $\rho$ ). We computed the average correlation over 25 of these random split iterations, yielding a final value of 0.76. This high consistency in object memorability indicates that, like full images, object memorability is a shared property across subjects. People tend to remember (and forget) the same objects in images, and exhibit similar performance in doing so. Thus memorability of objects in images can potentially be predicted with high accuracy. In the next section, we study the various factors that possibly drive object memorability in images.

## 3. Understanding Object Memorability

In this section, we aim to better understand object memorability and the factors that make an object more memorable or forgettable to humans. We first investigate the role that simple color features play in determining object memorability.

### 3.1. Can simple color features explain object memorability?

While simple image features are traditionally poor predictors of memorability in full images [Oliva, CVPR 2011], and with good reason [cite [11] from Oliva, CVPR 2011]], it is important to verify that this finding generalizes to individual objects. To do this, we first examined a number of simple color statistics. We decomposed each image into its hue, saturation, and value components and calculated the mean and standard deviation of each channel. Essentially no relationship existed between memorability and either mean hue ( $\rho = 0$ ) or mean saturation ( $\rho = 0.02$ ). This deviates somewhat from the findings related to images that show hue to be weakly predictive of memorability. However, this makes sense since the effect has been speculated to be due to the blue and green outdoor landscapes being less memorable than warmly colored human faces and indoor objects and people, outdoor scene-related image regions such

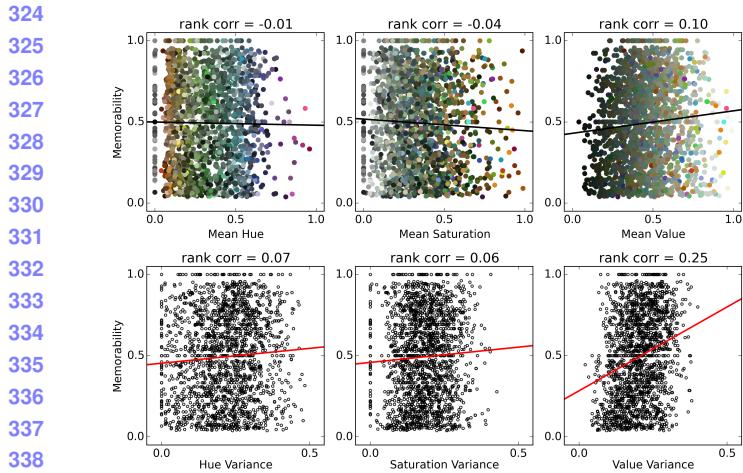


Figure 3: Correlations between simple color features and object memorability. Color features were computed from HSV representations of the objects.

as sky and ground were not included as objects. This may explain why the effect was not present in our dataset. Looking at the variance of each channel, we see that variance in hue ( $\rho = 0.16$ ) and saturation ( $\rho = 0.15$ ) are weakly correlated with memorability, while value has a medium correlation ( $\rho = 0.38$ ). This suggests that variation in the color hue and color purity of an object contribute somewhat to object memorability. This may be because people are memorable regardless of the color of their clothing, or simply that color inhomogeneity draws ones attention. The finding that variation in value contributes considerably to object memorability indicates that high contrast objects are more memorable. Although the correlation seems high compared to the performance of past simple features in past research, the scatterplot in FIGURE X suggests that it may not produce reliable predictions. Next, we computed image size, calculated by the number of pixels that make up the object normalized by the total number of pixels in the parent image. Not surprisingly, this metric correlated strongly with object memorability ( $\rho = 0.53$ ). This makes sense given that large objects, especially that take up the majority of the parent image frame, are more likely to be seen and identified.

### 3.2. What is the relationship between visual saliency and object memorability?

Note: add in small intro about past work

To examine the relationship between visual saliency and object memorability, we used two indexes of saliency to describe each object. The first was calculated as the number of unique fixation points within the area of each object. The correlation between object memorability and number of fixations within those objects was quite high ( $\rho = 0.71$ ). How-

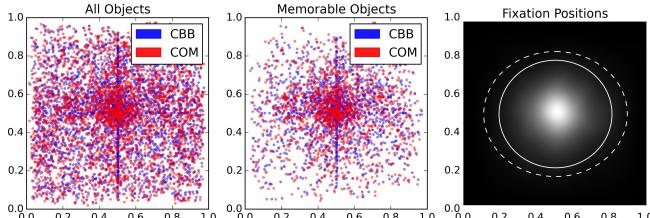


Figure 4: Positions. add-in later.

ever, this correlation decreases significantly as the number of total fixations within the object increases. In figure X, we show the correlation between object memorability and number of fixations for subsets of the objects that have at least some minimum number of fixations. On the leftmost side of the plot, the correlation is at it's highest since the set of objects with a fixation count greater than or equal to zero includes all objects and so the correlation is identical to FIGURE FIX-CORR. However, as the minimum number of fixations increases, we look only at objects that contain an increasingly higher number of distinct fixation points, and the correlation decreases. By the time we reach a minimum fixation count of around 35, the correlation falls to around 0.2. This may mean that the predictive value of saliency decreases when there are many areas of interest within a single object. (NOTE: We may want to show examples of images with lots of fixation points that were not well predicted. We could just plot the fixation locations as points on the image) The reason for this decline may be that...[make arguments here] Alternatively, FIGURE Z shows a similar relationship in which the correlation between memorability and fixation count is plotted as a function of minimum number of objects present in the parent image of the object. In a similar pattern, we see that as the minimum number of objects increases, the correlation between fixation count and object memorability decreases. This follows from the fact that fixation count and number of parent image objects are negatively correlated ( $\rho = -0.38$ ), meaning that if there are more objects in an image, there are less fixation points in any one object, which may a consequence of needing to distribute attention across the objects in the scene. In both scenarios, the ability to predict object memorability sharply decreases.

The second metric we used... (put map method here?)

### 3.3. What is the relationship between object memorability and object categories?

In the previous sections, we showed that simple features have little predictive power over object memorability and there exists a weak [JOSH: this might be too strong of a claim] relationship between visual saliency and object memorability. In this section, we show that object memora-

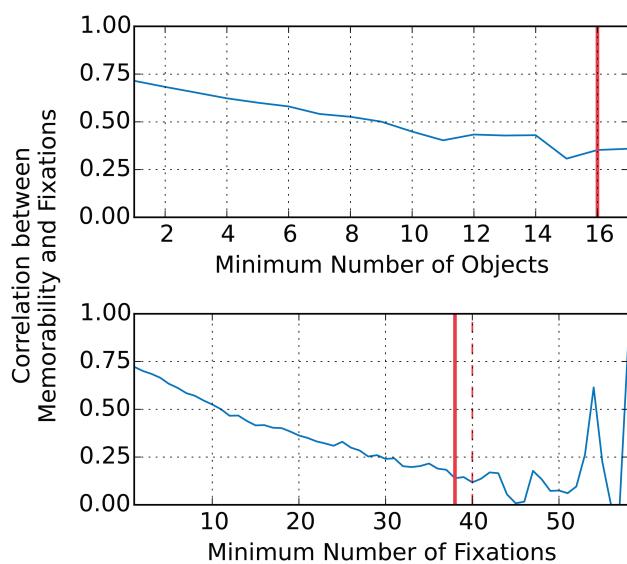


Figure 5: **Correlation between object memorability and number of fixations.** add-in later.

bility is heavily influenced by it's category and investigate the possible reasons why.

### 3.3.1 Are some object classes more memorable than others?

Our dataset contains 3414 object segmentations from the Pascal-S dataset. For this analysis, we first assigned three in-house annotators the task of assigning class labels to each object segmentation in our dataset. The annotators were given the original image (for reference) and the object segmentation and asked to assign 1 category to the segment out of 7 possible categories: animal, building, device, furniture, nature, person, and vehicle. We choose these high-level categories such that a wide range of object classes could be covered under these categories. For example, device included object segments like utensils, bottle, tv, computer etc, nature included segments like tree, mountain, flowers, and vehicle covered segments like car, bike, bus, aeroplane etc. **add a small table here which shows stats of the object classes n their frequency in the dataset.**

Figure 6 shows the average memorability score for the all 7 different object classes in our dataset. This visualisation gives a sense of how the memorability of different object classes differs. Animal, person, and vehicle are all highly memorable classes with each of them having an average memorability score greater than 0.5. Interestingly, all the other object categories have an average memorability score lower than 0.25 indicating that humans do not remember objects from these categories very well. In particular, furniture has an average memorability score of only 0.18 and

Object Class	Memorability of top 20 objects
Animal	0.94
Building	0.65
Device	0.86
Furniture	0.63
Nature	0.67
Person	0.93
Vehicle	0.96

Table 1: Average memorability of top 20 objects for each class

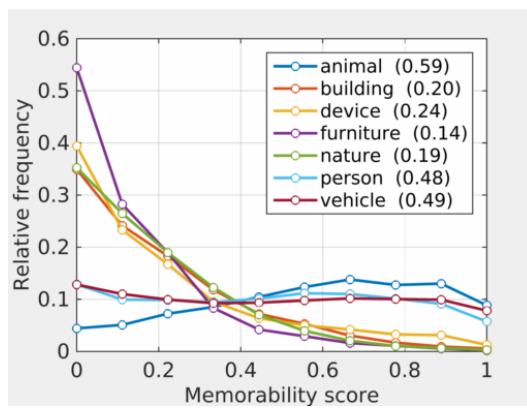


Figure 6: **Average memorability per object class.** Figure showing some object classes are more memorable than others.

is the least memorable object class. This could be possibly due to the fact that most objects from classes like furniture, nature, and building either appear mostly in the background or are occluded which could decrease their memorability significantly. On the contrary, objects from animal, person, and vehicle classes appear mostly in the foreground leading to a higher memorability score on average. Table 1 shows the average memorability of the top 20 most memorable objects for each object class. This analysis is particularly interesting as these top objects are not occluded and most of them tend to appear in the foreground. The top 20 most memorable objects from person, animal and vehicle have memorability higher than 0.90 whereas the average memorability of the top 20 objects from building, furniture, and nature is lesser than 0.70. While the differences in the memorability of different classes could be driven primarily due to factors like occlusion, size, background/foreground, the results in table 1 suggest that memorability could be an intrinsic property of an object class and some object classes like person, animal, vehicle are in general intrinsically more memorable than classes like furniture, nature etc.

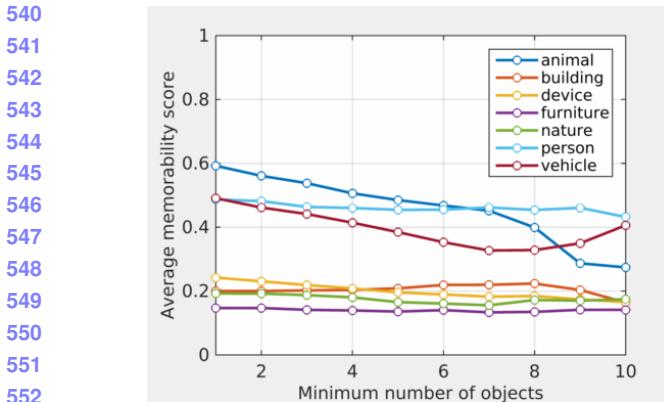


Figure 8: Correlation between object class and number of objects. add-in later.

### 3.3.2 Why are some objects not memorable within a class?

As demonstrated above, some object classes like animal, person, vehicle are more than others either due to their intrinsic property or external factors like occlusion, foreground/background etc. However, not all objects in a class are equally memorable. The examples in figure 7 show the most memorable and least memorable objects for each object class. A common property between these objects is that the least memorable objects within each object class tend to be occluded and obstructed by other objects. What other possible factors could influence the memorability of an object within a class?

**Relationship with number of objects in an image:** We first tested how the memorability of each object class is affected by the number of objects inside an image. We took in all images that had at least 'n' objects (where  $1 \leq n \leq 10$ ) inside them and computed the average memorability of each object class. Figure 8 shows the change in average memorability of the different object classes with respect to the increase in number of objects in an image. This figure shows that the number of objects present in an image is an important factor that results in the variation in the memorability of objects within a class. As the number of objects in an image increase, the memorability of the object classes decreases. In particular, the memorability of objects belonging to highly memorable classes like animal, person, and vehicle decreases significantly with the increase in number of objects in an image. Intuitively, this could mean that with an increase in number of objects, humans cannot concentrate on a single object in an image and have a difficulty remembering objects in those images. Thus, if a person, animal or vehicle is present in a highly cluttered image, humans can not remember those objects very well.

**Relationship of inter-class memorability:** While the previous analysis sheds light on how the memorability of an object class is effected by factors such as occlusion, and

number of objects in an image, how does the presence of a particular object class effect the memorability of another object class? To investigate this, for each possible pair of object categories we took all images that contained at least one object from both the categories and computed the average memorability scores for the two object categories. This way we were able to capture the relationship between pairs of object categories and how their presence effects their respective memorability scores. Figure 9 plots these results and for each object class, shows how it's memorability is effected in the presence of other object classes. The red mark on each line shows the over all average memorability of that class. Firstly, the memorability of low memorable classes i.e. nature, furniture, device, and building is not effected a lot in the presence of other object categories and their memorability tends to be low throughout. The memorability of person class also remains close to it's average memorability score and tends to be unaffected by the presence of most object categories. However, the memorability of person does get effected in the presence of buildings as the average memorability of person class drops below 0.4 for images containing both persons and buildings. This could be due to the fact that there exists images wherein the building is quite large and the persons in those images are usually smaller or less significant in contrast to the building (also illustrated in figure 10). The memorability of the animal class remains close to it's average memorability in presence of most classes, however it drops significantly to below 0.4 in presence of the person class (also shown in figure 10). The memorability of vehicle class is strongly affected by the presence of other object categories. In particular, it's memorability drops significantly in presence of person and animal classes also shown in figure 10.

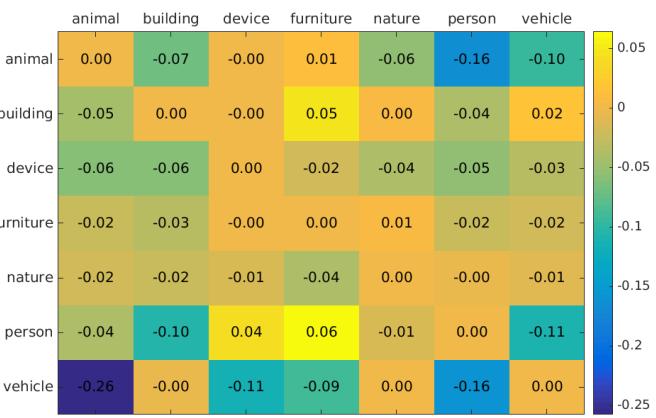


Figure 9: inter-class object memorability relationship. add-in later.

Taken together, the results from this section show that the memorability an object within a particular class is greatly effected by occlusion, number of objects present in an image and presence of other object classes in the image.

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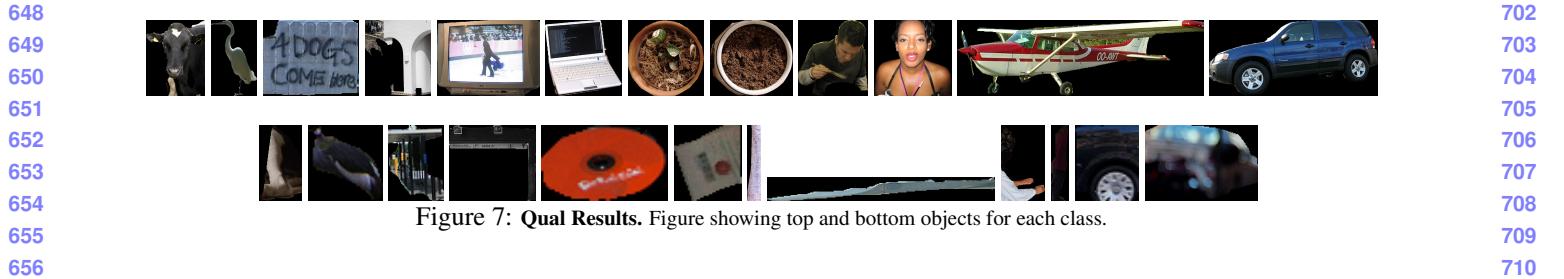


Figure 7: Qual Results. Figure showing top and bottom objects for each class.

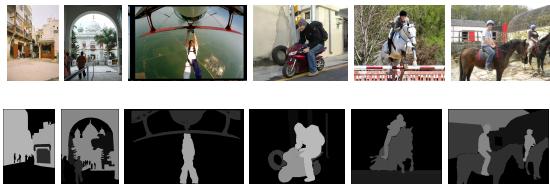


Figure 10: Qual Results. Figure showing how memorability of different classes is effected in presence of other classes. Bottom row is the memorability map

### 3.4. What is the relationship between object and image memorability?

[Note: only the skeleton of this section is added, this still needs significant work]

While in the previous sections, we have investigated the various factors that could effect object memorability, an important question remains. Now that we know what objects people remember and the factor that influence their memorability, how does the memorability of objects effect the overall image memorability? To shed light on the relationship between image memorability and object memorability, we conducted another large-scale experiment on Amazon Mechanical turk for the images in our dataset to gather their respective memorability scores. For this experiment, we followed the exact paradigm as the memory game experiment proposed in [5]. [add details about the fillers, add details about the experiment including number of workers, number of times each image was viewed by workers and explain the consistency analysis]

After collecting the image memorability scores, we conducted several analysis to answer - if an image is highly memorable, what happens to memorability of objects inside the image (and vice versa)? For each image in the dataset, we firstly computed the maximum object memorability within the image. Figure ?? shows the high correlation of maximum object memorability with image memorability ( $\rho = 0.43$ ). Although there is a high correlation between maximum object and image memorability, it still doesn't predict image memorability completely. However, table ?? also demonstrates that maximum object memorability is a very strong predictor of whether an image is highly memorable or low memorability. If we only take the topmost 20 and bottommost 20 images from the dataset, then their average max object memorability is highly corre-

Animal	Building	Device	Furniture	Nature	Person	Vehicle
0.38	0.22	0.47	0.53	0.64	0.54	0.30

lated with the image memorability scores. Similar trend is observed for 50 most and 100 most top and bottom memorable images. This is also shown via the figure XX [show the qualitative examples here to show memorable images contain memorable objects and non-memorable images do not]. This shows although simply the max object memorability cannot predict whether an image is medium memorable, max object memorability serves as a strong features in predicting if an image is highly memorable or not. Images that are lowly memorable, is possibly due to the fact that they do not contain a single highly memorable object [refer to qual figure again].

## 4. Predicting Object Memorability

here the benchmarking and baseline code comes up

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