What makes an object memorable?

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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.

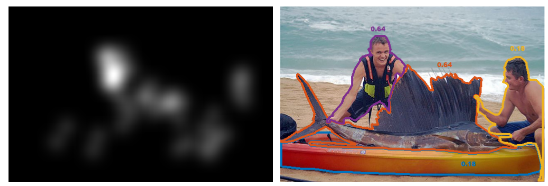

Figure 1: **Not all objects are equally remembered.** Memorability scores of objects for the image in the top row obtained from our pysophysics experiment.

1. Introduction

Consider the image and it's 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 use implicitly but others are dependent on more explicitly remembered information in 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 and interesting differences in memorability of objects in an image. Furthermore, the memorability of complex images may be principally driven by the memorability of it's objects. Can specific objects inside images be memorable to all us and how can we better understand what makes those objects more memorable?

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

Firstly, we show that just like image memorability, object memorability is a property that is shared across subjects and objects remembered by one person are also likely to be remembered by others and vice versa. Secondly, we show that there exists a strong correlation between visual saliency and object memorability and demonstrate insights when can visual saliency directly predict object memorability and when does it fail to do so. While there have been have a few studies that explore the connection between image memorability and visual saliency [2], [12], our work is the first to explore the connection between object memorability and visual saliency. Third, we explore the connection between image memorability and object memorability and show that the most memorable object inside an image can be a strong predictor of image memorability in certain cases. Studying these questions, help not only understand visual saliency, image and object memorability in more detail, but it can also have important contributions to computer vision. For example, understanding which regions and objects in an image are memorable would enable us to modify the memorability of images which can have applications in advertising, user interface design etc. With this in mind, as shown in the section 4, our proposed dataset serves as a benchmark for evaluating object memorability model algorithms and can help usher in future algorithms that try to predict memorability maps.

1.1. Related works

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

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

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

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

2. Measuring Object Memorability

As a first step towards understanding memorability of objects, we built an image database containing a variety of objects from a diverse range of categories, and measured the probability that every object in each image will be remembered by a large group of subjects after a single viewing. This helps provide ground truth memorability scores for the objects inside the images and allows for a precise analysis of the memorable elements within an image. For this task, we utilized the PASCAL-S dataset [9], a fully segmented dataset built on the validation set of the PASCAL VOC 2010 [3] segmentation challenge. For improved segmentation purposes, we manually cleaned up and refined the segmentations from this dataset. We removed all homogenous non-object or background segments such as ground, grass, floor, sky etc, as well as imperceptible object fragments and excessively blurred regions. All remaining object segmentations were tested for memorability. In the end, our final dataset consisted of 850 images and 3412 object segmentations i.e. on average each image consisted of approximately 4 object segments for which we gathered the ground truth memorability on.

2.1. Object Memory Game

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

Unknown to the subjects, inside each block, each sequence of images was pseudo-random and consisted of 3 'target' images taken from the Pascal-S dataset whose ob-

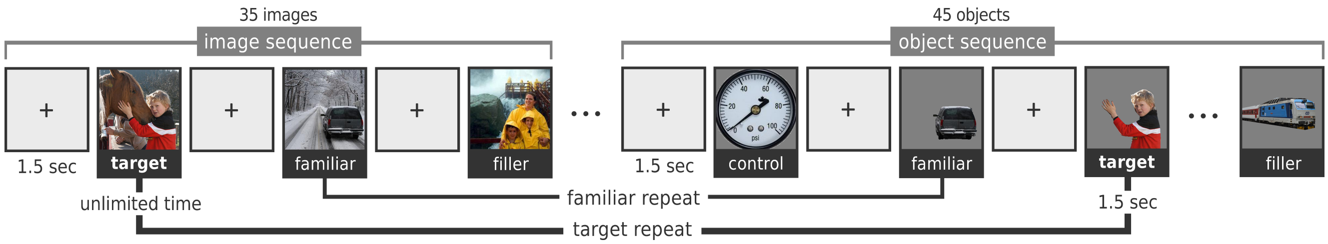

Figure 2: **Main task.** add-in later.

jects 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 [13] and the 'familiar' images were randomly sampled from the MSRA dataset proposed in [11]. 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 [10] 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 Spearmans rank correlation (ρ). 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 features explain memorability?

While simple image features are traditionally poor predictors of memorability in full images [5], and with good reason [8], do they play any role in determining object memorability? We decomposed each image into it's hue, saturation, and value components and calculated the mean and standard deviation of each channel. Mean value ($\rho = 0.1$) and variance in value ($\rho = 0.25$) were weakly correlated with object memorability suggesting that brighter and higher contrast objects may be more memorable (Figure 3). On the other hand, essentially no relationship was found between memorability and either hue or saturation (Figure 3). This deviates slightly from the findings in [5] that showed mean hue to be weakly predictive of image memorability. However, this makes sense since the effect was speculated to be due to the blue and green outdoor landscapes being less memorable than warmly colored human faces and indoor scenes. While our dataset contained plenty of indoor objects and people, outdoor scene-related image

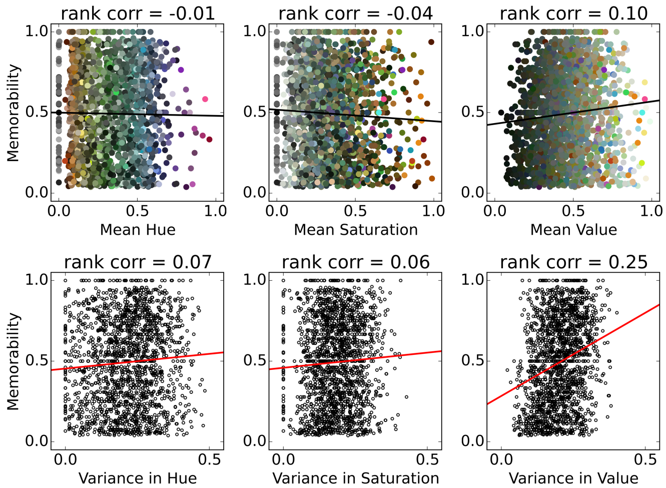

Figure 3: **Correlations between simple color features and object memorability.** Color features were computed from HSV representations of the objects.

regions such as sky and ground were not included as objects. Taken together, these results show that, like image memorability, basic pixel statistics do not play a significant role in determining the memorability of objects in images.

3.2. What is the role of saliency in memorability?

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 ($\rho = 0.71$). However, 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

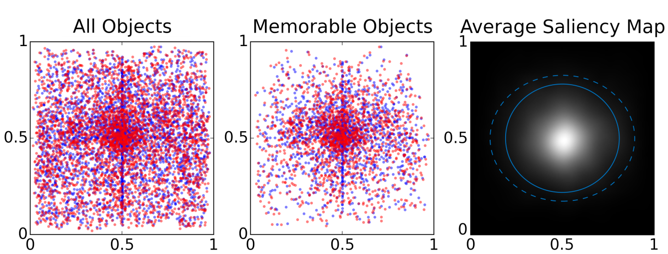

Figure 4: **Positions.** add-in later.

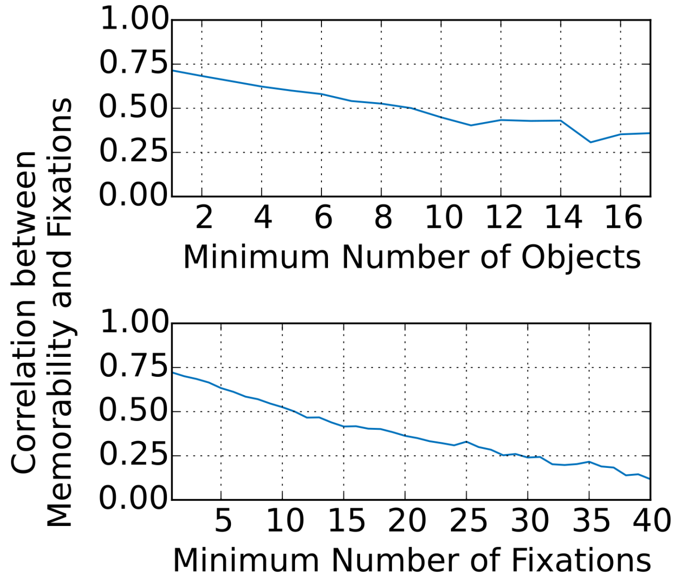

Figure 5: **Correlation between object memorability and number of fixations.** add-in later.

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 objet 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 memorability 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 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.

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

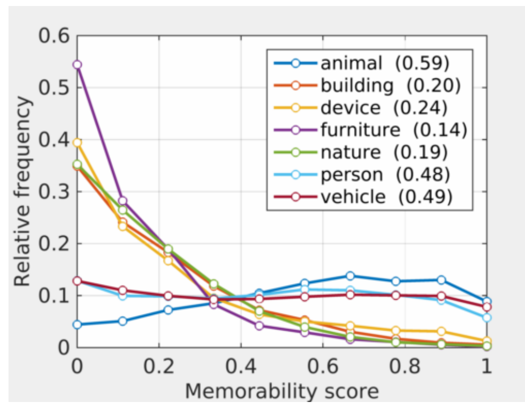

Figure 6: **Average memorability per object class.** Figure showing some object classes are more memorable than others.

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 $1 <= n <= 10$) 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

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

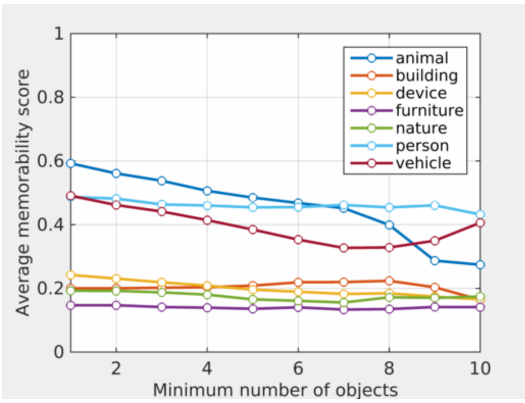

Figure 8: **Correlation between object class and number of objects.** add-in later.

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.

	animal	building	device	furniture	nature	person	vehicle
animal	0.00	-0.07	-0.00	0.01	-0.06	-0.16	-0.10
building	-0.05	0.00	-0.00	0.05	0.00	-0.04	0.02
device	-0.06	-0.06	0.00	-0.02	-0.04	-0.05	-0.03
furniture	-0.02	-0.03	-0.00	0.00	0.01	-0.02	-0.02
nature	-0.02	-0.02	-0.01	-0.04	0.00	-0.00	-0.01
person	-0.04	-0.10	0.04	0.06	-0.01	0.00	-0.11
vehicle	-0.26	-0.00	-0.11	-0.09	0.00	-0.16	0.00

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

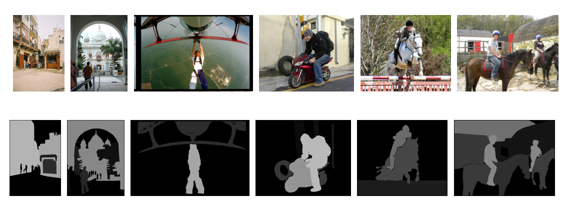

Figure 10: **Qual Results.** Figure showing how memorability of different classes is effected in presence of other classes. Bottom row is the memorabilty map

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.

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 remembers. 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 bottomost 20 images from the dataset, then their average max object memorability is highly correlated 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

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

References

[1] T. F. Brady, T. Konkle, G. A. Alvarez, and A. Oliva. Visual long-term memory has a massive storage capacity for object details. *Proceedings of the National Academy of Sciences*, 105(38):14325–14329, 2008. 3

[2] Z. Bylinskii, P. Isola, C. Bainbridge, A. Torralba, and A. Oliva. Intrinsic and extrinsic effects on image memorability. *Vision research*, 2015. 1, 2

[3] M. Everingham and J. Winn. The pascal visual object classes challenge 2010 (voc2010) development kit, 2010. 2

[4] P. Isola, J. Xiao, D. Parikh, A. Torralba, and A. Oliva. What makes a photograph memorable? *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 36(7):1469–1482, 2014. 1

[5] P. Isola, J. Xiao, A. Torralba, and A. Oliva. What makes an image memorable? In *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, pages 145–152. IEEE, 2011. 1, 2, 3, 7

[6] A. Khosla, J. Xiao, A. Torralba, and A. Oliva. Memorability of image regions. In *Advances in Neural Information Processing Systems*, pages 305–313, 2012. 1

[7] J. Kim, S. Yoon, and V. Pavlovic. Relative spatial features for image memorability. In *Proceedings of the 21st ACM international conference on Multimedia*, pages 761–764. ACM, 2013. 1

[8] T. Konkle, T. F. Brady, G. A. Alvarez, and A. Oliva. Conceptual distinctiveness supports detailed visual long-term memory for real-world objects. *Journal of Experimental Psychology: General*, 139(3):558, 2010. 3

[9] Y. Li, X. Hou, C. Koch, J. M. Rehg, and A. L. Yuille. The secrets of salient object segmentation. In *Computer Vision and Pattern Recognition (CVPR), 2014 IEEE Conference on*, pages 280–287. IEEE, 2014. 2

[10] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014*, pages 740–755. Springer, 2014. 3

[11] T. Liu, Z. Yuan, J. Sun, J. Wang, N. Zheng, X. Tang, and H.-Y. Shum. Learning to detect a salient object. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 33(2):353–367, 2011. 3

[12] M. Mancas and O. Le Meur. Memorability of natural scenes: the role of attention. In *ICIP*, 2013. 2

[13] C. Yang, L. Zhang, H. Lu, X. Ruan, and M.-H. Yang. Saliency detection via graph-based manifold ranking. In *Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conference on*, pages 3166–3173. IEEE, 2013. 3