Deep Multi-Modal Image Correspondence Learning

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Figure 1: Which of the four photographs corresponds to the left floorplan? The task requires careful and sophisticated human reasoning, unlike many other computer vision problems that only require instant human attention. This paper explores the potential of deep-neural networks in solving such a problem. The answer is in the footnote².

1 Introduction

Our world is full of imagery rich in modalities. Product manuals utilize stylized line drawings to emphasize product features. Building blueprints are precise technical drawings for construction design and planning. Artists use characteristics brush-strokes for unique aesthetic appeals. Humans learn to understand images of different modalities and associate them with the physical views through our eyes.

In a quest to reach the level of human visual intelligence, an important capability for computer vision is to associate images in different modalities. Surprisingly, apart from some notable exceptions [28, 10], cross-modal image association has been an under-explored problem in the field, while cross-modal data analysis has recently been popular,
for instance, between an image and natural language [17] or audio [4, 25].

In this paper, we learn to match a floorplan image and photographs of building interiors. We use a new large-scale database of 5 million floorplan images of residential units (mostly apartments) associated with 80 million photographs [1]. This is a challenging cross-modal image correspondence learning problem because 1) a floorplan is a stylized architectural drawing, only capturing rough geometric structure in an orthographic view, which is very different from a photograph; and 2) only a part of a floorplan image corresponds to each photograph (e.g., kitchen, bathroom, and living room).

We formulate and solve several variants of the cross-modal matching problem (see Figure 1). Specifically, we first consider the case where a single photograph (of known or unknown room type - living room, bathroom, bedroom etc.) needs to be matched to the floorplan. Thereafter, we consider the case where a set of photographs corresponding to different parts of the building need to be matched to the floorplan. The latter variant requires us to explore the use of different neural architectures for handling unordered sets of data-points. Our experimental results show that our models are extremely effective in discovering visual cues that associate floorplan images and photographs across vastly different modalities. In fact, our models outperform human subjects, who often need half a minute or more to solve each matching test.

The key contributions of this paper are: 1) we introduce a set of challenging multi-modal image-set matching problems to the community with human baselines obtained through Amazon Mechanical Turk (AMT); 2) we develop deep neural network based methods that outperform humans in all these tasks; 3) we analyze the behavior of different models by generating visualizations that provide intuitions as to how they reason the problem; and 4) we present applications enabled by this new capability to perform cross-modal matching between floorplans and photographs.

2 Related work

Image correspondence: Image correspondence has a long history in vision. While feature detection and matching techniques based on descriptors such as SIFT [22] and SURF [7] have been successful for narrow-baseline problems, they perform poorly for large-baseline problems. To overcome these problems, researchers have proposed detecting and matching larger-scale structure such as building facades for ground-to-aerial image matching [5, 29], or to learn the relationships of features across large-baselines (e.g., ground to satellite images) [18].

More recently, a number of neural network architectures have also been proposed for the problem. Long et al. used CNN to improve feature localization [21]. Siamese networks [9] and their variants have also become a popular architecture to learn distance metrics [14, 30, 19] between local image patches. Altwaijry et al. [2] extended the Siamese architecture with spatial transformer network [16] to perform feature detection as well as matching inside a network. All these methods focus on comparing images in a single modality (i.e., photographs). Our problem is fundamentally different in that we need to handle images in vastly different styles (floorplans vs. photographs) and viewpoints, and to reason with sets of different cardinalities.

Multi-modal matching: Multi-modal data analysis is becoming an increasingly active area of research. In the field of computer vision, Visual Question Answering is a notable example [3], where a model needs to jointly reason about the image and a natural language question to produce an answer. Image captioning has been another popular problem involving images and natural language [8]. Visual storytelling is its natural extension, where the task is to write a story given a set of images [15]. All these studies focus on multi-modal data analysis between images and a language, while we focus on multi-modal image analysis.

The closest work to ours is the cross-modal representation learning by Castrejón et al. [10]. They learn common scene representation across five different modalities, in particular, photographs, clip-arts, sketches, texts, and “spatial-text”. The key difference from our work is that they focus on classifying scene categories. Instead, we seek to classify instances of indoor scenes, requiring more precise geometric reasoning and content analysis. Furthermore, samples in their work are in one-to-one correspondence across modalities, and are spatially aligned. In our work, multiple samples in one modality as a whole (photographs) correspond to only one sample in the other (floorplan). This prohibits standard cross-modal representation learn-
ing as a single photograph is not equivalent to a single floorplan.

**Indoor scene understanding**: Matching photographs and floorplans has been an important problem in the context of indoor scene localization. Most existing techniques employ explicit geometry reasoning. For instance, Chu et al. [11] align visual odometry reconstruction against a floorplan. In addition to multi-view geometry, Martin et al. [24] exploit the order of photographs taken in an individual photo album to align photographs against a floorplan. Wang et al. [28] enable the alignment of a single image against a floorplan, via more sophisticated image understanding techniques involving scene layout, store boundaries, and texts. Liu et al. [20] employ similar image processing techniques to align a photograph to a floorplan of a residential unit. In all these works, a ground-truth floorplan is given, and the problem is to perform image localization via hand-coded features. In contrast, our work studies machine vision’s capability to automatically learn an effective representation that allows us to compare images of quite different modalities, floorplans and photographs.

### 3 Cross-modal image matching problem

This paper explores a diverse set of matching problems between floorplans and photographs, as shown in Figures 2 and 3. The basic problem configuration is to provide a model with one floorplan image and one photograph, and ask whether they come from the same apartment. For a comprehensive study, we investigate more problem variations by considering the following three problem settings.

- **First**, we vary the number of photographs for each apartment. For example, we may supply a bathroom photograph only, or bathroom, kitchen, and living-room photographs altogether.

- **Second**, we vary the number \( k \) of apartments or matching candidates. When \( k = 1 \), the model essentially answers a “Yes / No” question — if the floorplan matches the photograph or not. When \( k \geq 2 \), the model must choose the photograph that matches the floorplan from multiple choices.

- **Third**, we explore both room-aware and room-agnostic matching. Suppose we are to match a floorplan against a set of three photographs. In a case of room-aware matching, the network knows the room type for each photograph, and can train room-type specific network modules. In a case of room-agnostic matching, the network is given randomly ordered photographs without their room type information.

### 4 Neural cross-modal image matching

This section proposes our neural approach to the diverse family of cross-modal image matching problems. We provide details for some representative problem configurations; it is straightforward to construct the architecture for the remaining ones.

#### 4.1 Pair matching

This is the basic configuration. Given one floorplan image and one photograph, a network predicts if these two come from the same apartment. We formulate this as a similarity regression problem, where the output score ranges from -1 to 1. Inspired by the recent success of correspondence matching approaches [30, 14, 26, 19, 2], we form a
Siamese network followed by a fully connected regression network. The two arms of the Siamese network learn a feature representation of floorplans and photographs, respectively. We show the network structure in Figure 2. In a room-aware setting, we train a room-type specific encoder inside the Siamese network. In a room-agnostic setting, we train a single photograph encoder regardless of the room types.

We initialize each encoder with VGG16 [27], while changing the output feature dimension of \( fc6 \) to 512 and removing \( fc7 \) and \( fc8 \). The regression network consists of two fully connected layers. The first takes the concatenation of two feature vectors from the Siamese arms and outputs a 1,024 dimensional vector. The second layer regresses the similarity score. We follow [30] and use a hinge loss.

### 4.2 Photograph-set matching

As multiple photographs provide more cues in improving the matching accuracy, we consider the matching problem between a floorplan and a set of photographs of an apartment.

Suppose we have a set of \( n \) photographs (e.g., bathroom, kitchen, or living-room). A feature vector from the floorplan encoder and \( n \) feature vectors from the photograph encoders are concatenated into fully connected layers. Figure 3a shows our architecture for this problem.

In a room-aware setting, we always pass a set of photographs in the same order to the \( n \) encoders, allowing the network to optimize each encoder for each room-type. In a room-agnostic setting, we randomly change the order of photographs every time and let all the photograph encoders share the weights. This matching problem again has “Yes/No” answer, and a hinge loss is used.

### 4.3 \( k \)-way matching

Adding more photographs makes the matching problem easier. Adding more apartment candidates makes the problem more difficult. The \( k \)-way matching problem matches a floorplan to one of \( k \) photographs or \( k \) photograph-sets.

In a \( k \)-way photograph matching problem, we concatenate a feature from a floorplan and \( k \) features from photograph encoders that share the same weights. The concatenated features go through a classification network consisting of two fully connected layers. The final output is a one-hot encoding vector of size \( k \), indicating which of the \( k \) apartments matches the floorplan. A standard cross entropy loss is used in \( k \)-way matching problems. The architecture for \( k \)-way photograph-set matching similarly concatenates features from all the photographs and
all the apartments. We have not considered room-agnostic matching for \( k \)-way matching, as photographs of different room-types exhibit different amount of information, making the analysis of the matching-accuracy difficult.

5 Evaluations

In this section, we first describe the dataset and the implementation details, then demonstrate how our models perform in a variety of settings and compete against human vision.

5.1 Experimental setup

Data: We use the HOME'S dataset [1] throughout our experiments. It contains data for approximately 5 million apartments in Japan. Each apartment contains one floorplan image and a set of photographs annotated with room types. We have selected 100,000 apartments uniformly from the dataset, each of which has a floorplan image as well as bathroom, kitchen, and living-room photographs.

For pair matching problems, we form each training pair as a floorplan and a photograph(-set), either from the same or different apartments. The ratio of positive to negative samples is 1:1, making random guess a 50% chance. We have generated 99,000 training and 1,000 testing data.

For \( k \)-way matching problems, each training pair consists of one floorplan, one matching photograph from the same apartment, and \( k - 1 \) photographs from other apartments randomly sampled from the dataset. Random guess therefore has a \( 1/k \) chance. The numbers of training and testing examples are again 99,000 and 1,000, respectively.

Implementation details: We initialize each CNN encoder as a pretrained VGG16 model. For fine-tuning fully connected layers, we initialize the weights with a Gaussian function (\( \mu = 0 \) and \( \sigma = 0.001 \)). We resize floorplan images to \( 224 \times 224 \) to match the input of the original VGG16 model. For photographs, their original resolutions are usually around \( 100 \times 100 \). To save computational expenses, we resize them to \( 128 \times 128 \) instead of \( 224 \times 224 \). This makes the output of the final max-pooling layer a 8,096 = \( 4 \times 4 \times 512 \) dimensional vector, instead of 25,088 = \( 7 \times 7 \times 512 \). Therefore, we replace \( fc6 \) with a fully connected layer, which takes a 8,096 dimensional vector and outputs a 512 dimensional vector. We change the \( fc6 \) for the floorplan branch to output also a 512 dimensional vector. All \( fc6 \) outputs from both floorplan and photographs are concatenated and fed into the following fully connect layer which outputs a 1,024 dimensional vector. The last fully connected layer takes this 1,024 dimensional vector and make the final prediction (similarity score for pair matching and one-hot encoding for \( k \)-way matching). We have implemented our model using Torch7 [12] and trained our model on an Nvidia Titan X. Each model takes around 3 days to finish 50 epochs of training.

As discussed in Section 4, we vary the number of photographs per floorplan and the number of apartments in \( k \)-way matching, in addition to whether the model is room-aware or room-agnostic. In our experiments, the number of photographs per apartment is either 1 or 3. When set to 1, we choose the room-type of the photograph to be either a bathroom, a kitchen, or a living-room. When set to 3, these three room types are used altogether. We set the number of apartments in \( k \)-way matching to either 2, 4, or 8.

5.2 Results

Table 1 shows the primary results on our cross-modal image matching problems. For each of the 20 problem configurations, we divide the test set into 5 groups, and compute the average accuracy and the standard deviation of accuracy. Considering the difficulties in our matching problem, it is to our surprise that the network achieves more than 80% for most of the pair matching problems. It is also significantly higher than random guess in more difficult \( k \)-way problems. Comparing the numbers in the top two rows, room-aware networks can optimize feature encoders for each room type, and outperform room-agnostic ones consistently.

Human performance: We have conducted human tests on Amazon Mechanical Turk for representative problem cases. For each problem, we have generated 100 questions, and put 10 into one group. We have repeated the study until we get 3 answers to each of the question. In order to avoid spammy turkers, we have copied the first two questions to the end of the group (i.e., 12 questions in total), and only trusted workers who gave the same answers to these
12.5% for the pair, 2-way, 4-way, and 8-way problems, respectively. We have also conducted the same matching tests with human subjects on Amazon Mechanical Turk, where the green numbers show their performance.

| Matching type | Photograph type |
|---------------|-----------------|
|               | bathroom        | kitchen       | living room | all           |
| pair-agnostic | 81.2 ± 2.0      | 78.8 ± 3.7    | 76.0 ± 2.8  | 82.9 ± 2.1    |
| pair-aware    | 82.3 ± 1.6 (51.7) | 81.8 ± 2.1 (58.9) | 77.8 ± 1.8 (59.5) | 85.3 ± 3.4 (61.5) |
| 2-way         | 86.2 ± 1.4 (64.1) | 84.8 ± 3.5    | 81.2 ± 1.6  | 91.0 ± 1.5    |
| 4-way         | 72.4 ± 3.6 (43.0) | 72.4 ± 1.8    | 66.5 ± 1.7  | 77.8 ± 2.5    |
| 8-way         | 56.9 ± 1.8 (42.0) | 59.3 ± 1.9    | 54.0 ± 3.9  | 61.4 ± 2.5    |

Table 1: Matching accuracy. Columns specify the type of input photographs. Rows specify the matching problem type (pair or k-way and room agnostic or aware). For each experiment, we divide the testset into 5 groups, and calculated the average and the standard deviation across the 5 groups. The random guess has a chance of 50%, 50%, 25%, and 12.5% for the pair, 2-way, 4-way, and 8-way problems, respectively. We have also conducted the same matching tests with human subjects on Amazon Mechanical Turk, where the green numbers show their performance.

| Fusion layer | Fusion function | Averaging | Concatenation |
|--------------|-----------------|-----------|---------------|
| image        |                 | 77.9 ± 3.2 | 80.1 ± 3.2    |
| conv3        |                 | 81.0 ± 2.1 | 83.1 ± 2.3    |
| conv4        |                 | 82.7 ± 1.9 | 83.4 ± 3.5    |
| fc6          |                 | 84.2 ± 1.8 | 85.3 ± 3.4    |
| score        |                 | 84.7 ± 2.1 | 83.3 ± 2.8    |

Table 2: Performance of different fusion strategies on the set matching problem. We vary the fusion function and the layer in which we fuse the information of photographs. Fusing fc6 features via concatenation provides the best performance.

To our expectation, our matching problem is very challenging and human performance stays around 50% for most problems. Another interesting fact is that it requires 20, 30, and 50 seconds on average for workers to solve pair/2-way, 4-way, and 8-way matching problems, respectively. This is in contrast to most computer vision problems that require only instant human reasoning (i.e., one either knows the answer or not). In contrast, our network is able to answer a few dozen questions in a second for all these cases. This observation demonstrates that neural networks are also good at answering questions that require long periods of human reasoning.

**Exploiting multiple photographs:** As expected, the network is able to exploit more photographs to improve accuracy (See Table 1). We have explored other strategies of information merging by varying the layer in which we fuse the information from multiple photographs, either at the layer of images, convolutional features (conv3 and conv4), fully connected layer features (fc6), or predicted scores.

For the image layer, we fuse 3 photographs into a single 9-channel photograph. For the layer of convolutional features, we stack all the feature maps. For the layer of fully connected features, we concatenate feature vectors. For the layer of predicted scores, we add one more fully connected layer that computes their weighted average.

Table 2 shows matching accuracies over these four variants as well as the numbers when we simply take the average image, feature map, feature vector, or score. As three photographs are not spatially aligned, fusing misaligned information at an early stage poses unnecessary challenge for the network. On the other side, fusing only at the end fails to exploit mutual information properly. The optimal configuration is to fuse information at the (fc6) layer, where the feature vector encodes the information of an entire image.

**Room-awareness fine-tuning:** The room-aware networks consistently outperform the room-agnostic ones as the network can learn separate encoder for each room type. Table 3 studies the effects of room-aware fine-turning for the pair matching problem with a photograph-set. The first and the third rows are the new additions to Table 1. The
Table 3: Performance on the pair matching problem with the photograph-set. We vary whether to supply room type information, and whether and where to finetune the network. Finetuning a room-aware network provides the best performance.

| Fine-tuning                                  | Accuracy   |
|----------------------------------------------|------------|
| none (fixed to VGG)                          | 69.5 ± 2.9 |
| room-agnostic                               | 83.7 ± 3.0 |
| room-aware (only at fully connected)        | 84.1 ± 1.4 |
| room-aware                                  | 85.3 ± 3.4 |

Table 4: Performance of the models trained by different problems. The network learns fundamentally the same cross-modal similarity metric. We have used the models trained by four different problems (rows) to solve the three $k$-way matching problems (columns). We do not evaluate models trained on a $k$-way problem for $k'$-way problem when $k < k'$, because it is hard to exclude the bias. Please see Section 5.2 for details.

|                | Training | Evaluation |
|----------------|----------|------------|
|                | 2-way    | 4-way      | 8-way      |
| pair           | 87.8 ± 2.6 | 73.4 ± 3.6 | 57.0 ± 3.3 |
| 2-way          | 86.2 ± 1.4 | N/A        | N/A        |
| 4-way          | 87.4 ± 1.7 | 72.4 ± 3.6 | N/A        |
| 8-way          | 86.3 ± 1.0 | 71.8 ± 2.9 | 56.9 ± 1.8 |

Effective learning: The network fundamentally learns the same similarity metric between a floorplan and a set of photographs in our family of problems. A natural question is then to ask if one problem configuration is more effective than others in learning the metric. To understand this, we use the $k$-way matching problems to compare the accuracy of models trained on different problem configurations (see Table 4). More precisely, we have used pair (room-aware), 2-way, 4-way, and 8-way matching problems with a bathroom photograph to train networks.

Figure 4: Visualization for the receptive field of the final prediction. In each row, from left to right we show an input floorplan, an input photograph, and the corresponding receptive field visualization. Networks learn to localize which part of the floorplan the photograph corresponds to, for bathrooms (the first two rows), kitchens (the third row), and living rooms (the fourth row).
trained on the 4-way problem is used to solve only the 2-way problem.

The table shows that while trained problems vary in their difficulties, all the matching accuracies are very similar and do not exhibit statistically significant differences. This result suggests that, at least for our problem, one can effectively train a network with the smallest problem setting, the pair matching problem.

6 Model interpretation

Visualization of convolutional networks has been an active area of research [31, 13, 23, 32]. We extend the technique proposed by Zhou et al. [32] to analyze how our pair matching network learns to associate floorplan images and photographs across modalities. We show some results in the main paper, and refer more to the supplementary material.

Room localization: We adapt the idea in [32] to visualize the learned Receptive Fields (RFs). The difference is that we have two Siamese arms (modalities), instead of only one for their classification task. Our approach is to add noise to one arm while fixing the other. More specifically, in a sliding window manner, we fill a $11 \times 11$ window on a floorplan image with random noise drawn from normal distribution ($\mu = 0$ and $\sigma = 1$). The top two examples in Figure 4 show the result for a pair matching network with a bathroom photograph. The third example is with a kitchen photograph and the fourth is with a living room photograph. The network clearly learns to attend to the corresponding room region in a floorplan. We have conducted the same visualization test for roughly 50 examples for each room type. We have observed similar results 40% of the time.

Object discovery: The RF visualization indicates that the network learns to attend to the informative regions on the floorplan to make the prediction. However, it is...
still mysterious how the network manages to achieve such high matching accuracy, much higher than humans. What has also caught our attention is that the network has consistently recorded better accuracy with a bathroom or a kitchen over a living room. Our hypothesis is that the network learns to detect objects, such as washing basins, bathtubs, or cooking counters, in both the photograph and the floorplan; it then establish correspondences over the detections. We validate this hypothesis by manually editing the image and observing how the similarity score changes. As shown in Figure 5, at the bottom row, we have manually edited the floorplan to remove the washing basin, and have similarly removed it from the photograph by using PatchMatch software [6]. The figure shows the similarity score for every pair, which clearly indicates that the network uses the presence of an object and an object-icon to make the prediction. Please refer to the supplementary material for more examples.

7 Applications

In addition to the floorplan-to-photograph matching problem, the trained networks enable novel applications.

Image placement: Giving a sense of a place to live is a critical goal of a real estate website. While a floorplan and a set of photographs serve the purpose to some extent, this is still a challenging task for real estate websites. The success of the RF visualization in Section 6 enables a simple but effective algorithm to achieve this aim by placing photographs or indicating their locations over a floorplan, where the field response is the maximum (See Fig.6).

Image retrieval: An apartment listing without any photographs is even more difficult to imagine a sense of a place. Our network, given a floorplan image, can show likely appearance of the indoor space through image retrieval. More precisely, we use a pair matching network to identify photographs with high similarity scores. Figure 7 shows the top six bathroom photographs with the highest similarity scores with ground truth on the left. Notice that all retrieved photographs exhibit consistent appearance and content.

Localization: The simplification visualization technique in [32] suits our problem perfectly, since image segmentation is highly effective for floorplans that originate from vector graphics. The technique allows us to localize an exact image region that corresponds to a photograph in addition to its rough location. We use Photoshop to segment the floorplan image as shown in Figure 8. We then repeat removing a segment that has the least change in the similarity score. As Figure 8 demonstrates, this simplification process often produces correct image segments corresponding to the room of a photograph.
Figure 8: The simplification technique [32] is particularly effective for floorplan images, enabling the localization of an exact image region corresponding to the photograph. Here we show three results side by side. The first row contains: left) the floorplan, middle) the image, right) the segmentation result. Images below show the simplification process indicated by blue arrows.

8 Conclusions

This paper has introduced a novel multi-modal image correspondence problem with human baselines. This is a very challenging problem that requires long periods of reasoning even for humans, unlike other conventional computer vision problems that only require instant human attention. We have explored various deep network architectures for this task, and demonstrated that they achieve high matching accuracies, significantly outperforming human subjects. We have conducted a wide range of qualitative and quantitative experiments, and analyzed and visualized the learned representation. Lastly, we have shown a few applications utilizing the power of trained networks which have been otherwise impossible. We believe that this paper provides a new insight in the machine vision’s capability of cross-modal image matching, and promotes future research in this under-explored domain.

9 Acknowledgement

This research is partially supported by National Science Foundation under grant IIS 1540012 and IIS 1618685, Google Faculty Research Award, and Microsoft Azure Research Award. Jiajun Wu is supported by an Nvidia fellowship. This research was partially conducted while Jiajun Wu was interning at Microsoft Research. We thank Nvidia for a generous GPU donation.
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