

# Weakly-Supervised Learning of Dense Functional Correspondences

Stefan Stojanov\* Linan Zhao\* Yunzhi Zhang Daniel L. K. Yamins Jiajun Wu  
Stanford University

## Abstract

*Establishing dense correspondences across image pairs is essential for tasks such as shape reconstruction and robot manipulation. In the challenging setting of matching across different categories, the function of an object, i.e., the effect that an object can cause on other objects, can guide how correspondences should be established. This is because object parts that enable specific functions often share similarities in shape and appearance. We derive the definition of dense functional correspondence based on this observation and propose a weakly-supervised learning paradigm to tackle the prediction task. The main insight behind our approach is that we can leverage vision-language models to pseudo-label multi-view images to obtain functional parts. We then integrate this with dense contrastive learning from pixel correspondences to distill both functional and spatial knowledge into a new model that can establish dense functional correspondence. Further, we curate synthetic and real evaluation datasets as task benchmarks. Our results demonstrate the advantages of our approach over baseline solutions consisting of off-the-shelf self-supervised image representations and grounded vision language models.<sup>1</sup>*

## 1. Introduction

Finding pixel correspondence across image pairs is fundamental for object understanding and is critical for applications like shape reconstruction [39, 43, 46, 72], editing [19], and object manipulation in robotics [17, 28, 29, 55]. This task requires reasoning beyond visual similarity in local appearance, geometry, and texture across images. It also involves structural similarity, e.g., the part-whole relationships of objects and their part components, and semantic similarity, e.g., the functional properties of parts of objects.

These aspects of similarity are essential for learning efficient generalizable systems for downstream applications. For example, in imitation learning in robotics, human demonstrations are a scarce and valuable data source.

\*Equal contribution.

<sup>1</sup>Project website: <https://dense-functional-correspondence.github.io/>

Given a demonstration with an object, such as pouring with a kettle, establishing dense functional correspondence with another object that supports this function, e.g., a bottle, enables the efficient transfer of the demonstration.

It becomes harder to find dense correspondence when the input images shift from being two views of the same object to different objects from the same category, and finally to objects from distinct categories, as the visual similarity becomes less apparent. This work focuses on the most challenging scenario with objects from different categories. We aim to establish dense pixel-level correspondence between pairs of images containing objects with parts whose shape enables the execution of similar functions. Specifically, by “function”, we refer to the effect one object can have on another object or substance, e.g., the function “cut-with” for a knife and a spatula or “hang-onto” for objects with hooks.

Practically, training and evaluation for this task are challenging due to the lack of labeled data. Supervised training at scale is infeasible because manual dense correspondence labeling is intractable, emphasizing the need for a self- or weakly-supervised approach. For evaluation, while datasets exist for dense within-category correspondence [34, 68, 77] and sparse functional keypoint correspondence across categories [37], there is still no established task or dataset for dense correspondence across categories. In this work, we make progress toward addressing both the challenges of training and evaluation.

The key insight behind our training approach is that the capabilities of self-supervised image representations like DINOv2 [54] or Stable Diffusion [62] and vision language models (VLMs) [24, 78] are complementary but individually insufficient for solving this task. On the one hand, surprisingly accurate dense correspondences can be established using image features from pre-trained self-supervised models. This works well when the input images contain visually similar object instances from the same category, e.g., two cats or two cars [87]. However, the accuracy decreases for the more generic scenario when objects come from distinct categories. On the other hand, VLMs can detect the bounding boxes of object parts with similar functions in a zero-shot manner [24, 78] but cannot perform fine-grained reasoning about correspondences across objects.

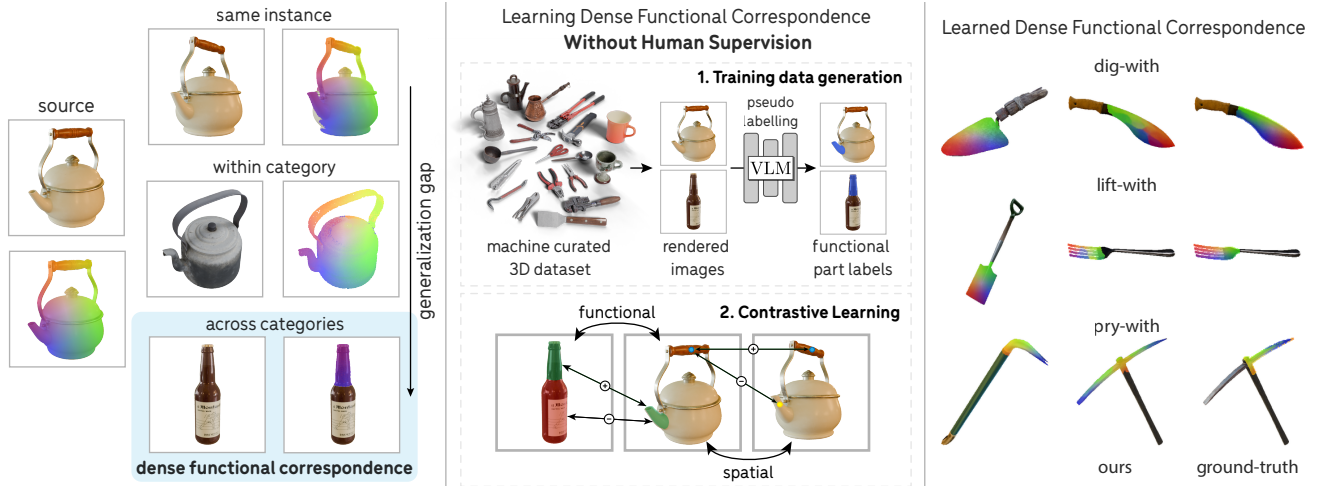


Figure 1. **Dense Functional Correspondence** refers to establishing dense correspondences across object instances based on function similarity (e.g., “pour-with”). This task is especially challenging when objects have visually different but functionally similar parts, requiring both semantic understanding, *i.e.*, identifying which parts can perform the same function, and structural understanding, *i.e.*, establishing dense correspondence across the parts at a surface-point-level based on functionally equivalent alignment. We propose a method to learn such correspondences with little human supervision, leveraging automated data curation and annotation, and dense contrastive learning.

We distill the strengths of each approach into a new model using a scalable technique that requires minimal human supervision. Specifically, we first obtain multi-view-consistent pseudo labels of functionally relevant regions of 3D object assets [7] using an off-the-shelf grounded VLM [78]. We then combine these labels with multi-view correspondences [17, 64] in a contrastive learning framework building on pre-trained DINOv2 [54] feature extractor. For evaluation, we define the dense functional 2D correspondence task and develop an annotation procedure based on aligning 3D object pairs in functionally equivalent poses.

In sum, we define the task of dense functional correspondence as a means for investigating cross-category dense correspondence. We then curate synthetic and real-world evaluation datasets for this task. We further propose a scalable, weakly-supervised method leveraging vision foundation models, which empirically outperforms baselines.

## 2. Related Work

Learning representations to establish dense functional correspondence requires fine-grained structural and semantic visual reasoning about objects. The most relevant prior works come from the object-level correspondences and affordance learning research domains. We also review recent work on vision foundation models and VLMs, focusing on works relating to fine-grained object understanding.

**Learning Correspondences.** For this work, it is relevant to categorize correspondence learning methods based on their degrees of generalization. For generalizing across geometric scene transforms, works on multi-view correspondences aim to match different views of the same scene [27, 63, 65], whereas optical flow techniques match consecu-

tive video frames [25, 26, 69]. For generalizing within categories, NOCS-style representations [34, 76, 77] enable dense matching across instances of a category, whereas learning sparse keypoints [47, 66] enables sparse matching based on pre-defined semantic keypoint taxonomies. For generalizing across categories, Lai et al. [37] propose matching based on object function by learning five keypoints per object function category. The main drawback of keypoint-based correspondences is the requirement for a keypoint taxonomy, which by definition limits such techniques’ capability to capture nuanced similarities across highly dissimilar objects (e.g., a bottle and a kettle). Through our dense functional correspondence formulation, we overcome the limitation of keypoint definitions and enable higher precision in downstream applications.

**Learning Affordances.** In his seminal work [18], James J. Gibson defines affordances as objects’ “opportunities for interaction.” Various object affordance formalisms have been developed in computer vision and robotics, such as estimating grasps [2, 16, 48, 49], and localizing affordance regions in 2D [5, 14, 44, 50–52] and 3D [10, 20, 83] through bounding boxes and segments [14, 50–52], heatmaps [10, 44, 50] or keypoints [58, 73, 81]. Early works adopt a fully supervised learning paradigm [2, 14, 50], while more recent works aim to use less supervision by learning from human object interaction videos [51], egocentric videos [41] or unlabeled exocentric images [40, 44]. Our work has two key distinctions: First, affordance heatmaps or segments identify object regions or parts in individual images. They do not allow for fine-grained spatial correspondence across object parts in different images (e.g., can identify the blades of two knives but cannot find correspondences for pixels be-

tween the tips or edges of the blades). Second, our focus is on object function – the effect an object can cause on something else, rather than the broader concept of affordance, which emphasizes potential interactions with a specific object instance (*e.g.*, striking with a hammer vs. holding). Last, our goal is to learn dense functional correspondence in a weakly-supervised manner, without relying on human annotations of ground-truth correspondences.

**Vision Foundation Models.** Recent developments in large-scale language [11, 60, 71] and image [59, 86] pre-training have led to the development of vision-language models (VLMs) capable of strong zero-shot performance through vision-question answering [42, 78], which have been adapted to reasoning about functional affordances and grasping in robotics [13, 24, 57, 85]. Powerful correspondence representations have been found to emerge [1, 67] in DINO [3, 54] and Stable Diffusion [62], which have led to direct applications in low-shot affordances [29] and object manipulation [12, 29, 35, 55, 56]. In this work, we leverage the complementary characteristics of VLMs and self-supervised image models to go beyond their individual capabilities for dense functional correspondence.

### 3. Dense Functional Correspondence

Distinct object categories with similar functionality, *e.g.*, a “kettle” and a “bottle” which can both pour liquid, may have different visual shapes and appearances as well as distinct part organizations. However, individual parts that serve the specific functionality of interest, *e.g.*, the spout of a kettle and the mouth of a bottle in this example, have a higher resemblance with each other than at the overall object level. Such consistency is a consequence of how form follows function – object parts that fulfill a specific function tend to remain consistent across objects, even if other parts vary greatly in shapes and arrangements. The part-level consistency provides a crucial ground from which we can derive the definition of functional correspondence (Section 3.1) and develop a corresponding evaluation data curation pipeline to benchmark this task (Section 3.2).

#### 3.1. Problem Definition

We refer to the effect that an object causes on other objects or substances as an “object function.” This concept has been widely studied in model generalization in visual computing [36, 37, 70, 89] and the development of categorization in humans [31, 38, 79]. Examples are shown in Figure 1, *e.g.*, “pour with.” When executing a function with an object, such as pouring with a kettle, the functional part (the spout) follows a specific 3D trajectory. To replicate this function with a different object, *e.g.*, a bottle, the neck of the bottle would be aligned with the spout and follow the same trajectory. This illustrates how the *same* object function is fulfilled with *different* objects via aligning function-

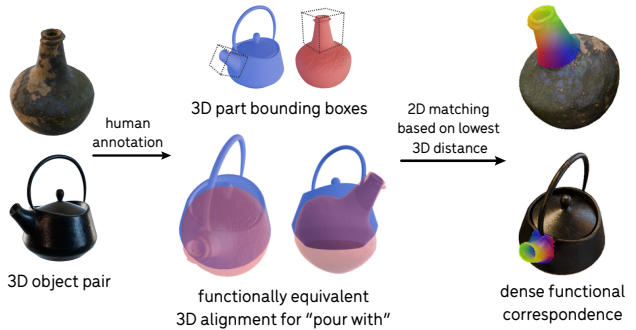


Figure 2. **Annotation Pipeline (Evaluation Only).** Given a 3D object pair (left) and a function (“pour-with”), we annotate the functional alignment of two objects by aligning the functional parts in 3D (middle). Afterward, we derive dense 2D correspondences (right) based on 3D distances of corresponding object surface points, with matching pixels shown in the same color.

ally equivalent parts, which is central to robotic applications with imitation learning approaches [23, 55, 90].

The above observations lead us to define dense functional correspondence through *3D object alignment based on functionally equivalent parts*. Specifically, given two objects (*e.g.*, a kettle and a bottle) and an object function (*e.g.*, “pour with”), the objects are aligned if and only if the parts that fulfill this function (*e.g.*, the kettle spout and the bottle neck) are spatially close to each other. The alignment induces an image-space distance: for any pair of pixels on the functional parts of two objects, the pixels are in *functional correspondence* if their respective surface points are close in 3D when the objects are aligned. Since this distance is defined at the pixel level, it is inherently *dense*.

Formally, the input consists of an object function  $\mathcal{F}$  and an image pair  $(I_1, I_2)$ , where each image is a view of a 3D object  $O_1$  and  $O_2$ . Let  $\pi^{-1} : I \rightarrow O$  represent the back-projection function that maps an image pixel to the corresponding 3D object surface point. We define  $M(O; \mathcal{F})$  as the functional part of object  $O$  responsible for executing  $\mathcal{F}$ , and let  $M(I; \mathcal{F})$  be its projected 2D mask in the image. In our setup, the functional parts of both objects,  $M(O_1; \mathcal{F})$  and  $M(O_2; \mathcal{F})$ , are assumed to be aligned in 3D such that they follow the same trajectory when performing  $\mathcal{F}$ . We therefore define *dense functional correspondence* as a mapping  $f(I_1, I_2; \mathcal{F}) : M(I_1; \mathcal{F}) \rightarrow M(I_2; \mathcal{F})$  that minimizes  $\sum_{p \in M(I_1; \mathcal{F})} \|\pi^{-1}(p) - \pi^{-1}(f(p))\|_2$ . This ensures that pixel pairs in functional correspondence are from spatially close locations in 3D when the objects are aligned.

#### 3.2. Evaluation Dataset Curation

The problem definition in Section 3.1 provides a guiding principle to obtain ground truth annotations for dense functional correspondence in image pairs by *aligning objects in 3D*. We introduce the annotation procedure and use it to construct both synthetic and real-world evaluation datasets for quantitative evaluation in Section 5.

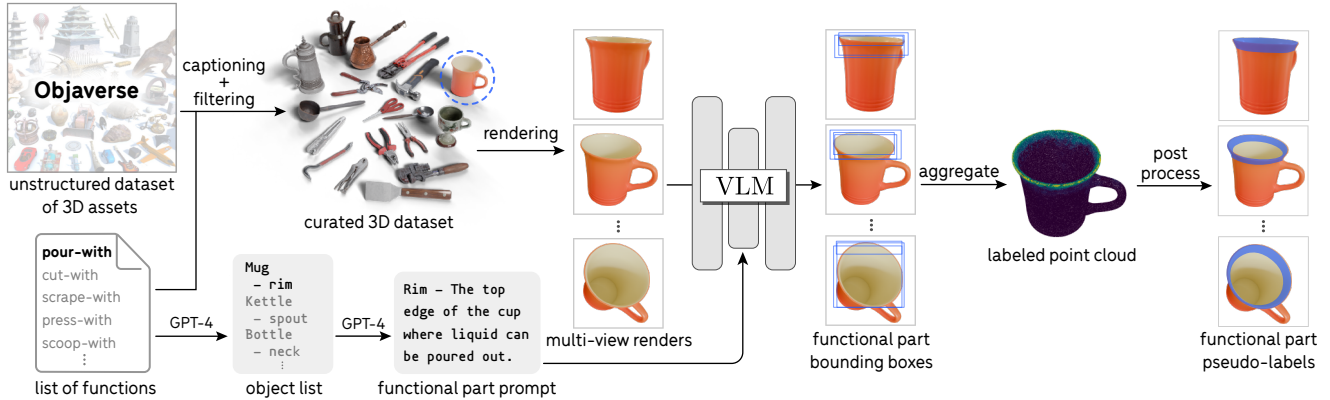


Figure 3. **Training Data Curation via VLM Pseudo Labeling.** Given a large unstructured dataset like Objaverse [7], we leverage off-the-shelf VLMs to curate and label the functional parts. Specifically, GPT-4 [53] generates category-specific functional part prompts, and CogVLM [78] produces bounding box proposals for multi-view image renderings, which are aggregated onto a 3D point cloud. The point cloud is post-processed to produce pixel-level functional part labels for training.

**Annotation Procedure.** To obtain ground-truth functional correspondence for an image pair, we assume each object is rendered from a known 3D asset. By aligning the two assets in 3D, we derive dense pixel correspondences between the images. This procedure eliminates the need for manual dense 2D labeling, enabling large-scale evaluation. An overview is shown in Figure 2.

Specifically, given two 3D meshes of objects supporting the same function, we first align them based on their functional parts and annotate a 3D bounding box around each functional part. Then, for a pair of rendered images, we unproject pixels from the functional parts onto the object surfaces and compute 3D distances between these points to perform minimum-cost matching. Pixels corresponding to visible surface points that are spatially close in 3D are matched. A detailed description of the annotation procedure is provided in the Supplement.

**Synthetic Evaluation Dataset.** We use the 3D assets from Objaverse [7], a large collection of diverse 3D models, to obtain a synthetic evaluation dataset. We hand-label 3D annotations for 950 pairs of assets from Objaverse spanning 24 functions, selected for quality and diversity. See Section 4.1 for how the assets and functions are selected. As such, 85% of the ground-truth pairs contain across-category correspondences. From these 3D annotations, we derive 1,800+ unique 2D image pairs rendered from the 3D assets, with ground truth dense functional correspondences.

**Real Evaluation Dataset.** Setting up a real-world benchmark is crucial for measuring model performance on real images. Thus, we utilize the HANDAL dataset [20], which contains images and 3D reconstructions of real-world objects. After manually fixing the geometry of the 3D scanned assets, *e.g.*, the missing concavities of mugs, pots and pans, we label 190 asset pairs spanning 13 functions. This results in a real evaluation dataset of 500+ unique 2D real image pairs with ground-truth functional correspondence labels.

## 4. Approach

Our goal is to develop a scalable learning framework for dense functional correspondences without relying on human-labeled ground truth. Since this task requires both semantic and structural knowledge, we distill from off-the-shelf VLMs to obtain pseudo-labeled training data (Sec. 4.1), which is further combined with dense spatial correspondences from synthetic data in a contrastive learning framework (Sec. 4.2). This approach enables the model to generalize to real-world data, as we will show in Sec. 5.

### 4.1. Dataset of Pseudo-labeled Functional Parts

A dataset for learning dense functional correspondences at scale requires a diverse source of object images, a diverse taxonomy of functions and associated functional parts, and a low-cost, reliable means for part labeling.

**Image Data.** Our approach requires a large and diverse multi-view image dataset where functional parts are visible. Existing multi-view object datasets [61, 80, 84, 88] are suboptimal because they have few desired objects like tools and utensils, the objects are in canonical poses that may not reveal functional parts, or are placed in cluttered contexts where occlusions often occur. To overcome this, we render high-quality images from the Objaverse [7] dataset using ray-tracing and HDRI environments [21] in Blender [6], obtaining arbitrary amounts of diverse multi-view data.

**Object and Function Taxonomy.** To curate relevant object assets for our training dataset, we prompt GPT-4 [53] for common functions and refer to object functions studied in [37, 49]. Then, we prompt GPT-4 to generate a comprehensive list of object categories for each function. After deduplication and manual filtering, our taxonomy has 24 functions and 160 object categories.

**Object Asset Selection.** To retrieve relevant assets from the noisy-labeled Objaverse dataset based on the list of object

categories, we utilize asset captions from Caption3D [45]. We use Llama 3.1 [15] to summarize the captions into category names and use Llama word embeddings to match the summaries to our category list. Finally, we prompt Llama to verify these matches. To ensure diversity, we cap each category at 200 assets. To ensure quality, we manually filter the retrieved assets to obtain 8,285 assets in total, 80% of which are used for training. Details about prompting, filtering, and the taxonomy are included in the Supplement.

**Functional Part Pseudo-Labeling.** Labeling data at scale using large pre-trained models has been shown as an effective approach for achieving high performance with minimal human effort [75, 82]. The key elements for success are a sufficiently accurate pre-trained model and a low-cost and reliable procedure for rejecting low-quality labels. Grounded VLMs [8, 42, 78] have shown remarkable capabilities for zero-shot prompt-based object detection. We, therefore, use the 17B grounded CogVLM [78] model, which has state-of-the-art referring expression detection performance. For an overview of the pseudo-labeling pipeline, see Figure 3. Given our list of object categories and functions, we prompt GPT-4 to obtain the names and appearance descriptions of functional parts to serve as prompts for CogVLM, which we then manually filtered and deduplicated. Because functional part names can be different across categories (*e.g.*, the spout of a kettle vs. the neck of a bottle), we generate these functional part lists separately for each category. We empirically found that prompting CogVLM with part names and appearance descriptions significantly improves the bounding box predictions.

Given a set of rendered views for an object and a functional part text prompt, we generate bounding box predictions with CogVLM [78], which vary due to sampling in VLM inference. The accuracy of the bounding boxes also depends on viewpoint because of part pose and visibility. To aggregate these possibly noisy labels and obtain a final part label, we sample a dense point cloud on the surface of the object, and accumulate the 2D labels across views onto the 3D points. We post-process these labeled point clouds to generate 2D masks for views rendered for training.

This dataset curation and pseudo-labeling procedure allows us to generate a large dataset of functional part segmentation labels with relatively little human effort, which was mostly necessary for prompt engineering and quality control. In this work, we apply this approach on the  $\approx 600\text{K}$  labeled meshes from Caption3D, but it is straightforward to scale up to the millions of meshes in Objaverse-XL [9].

## 4.2. Learning Dense Functional Correspondence

To learn dense functional correspondence, we train a feature embedding that captures both the high-level function semantics and the structural similarity between functional parts. For instance, given a bottle and a kettle for the func-

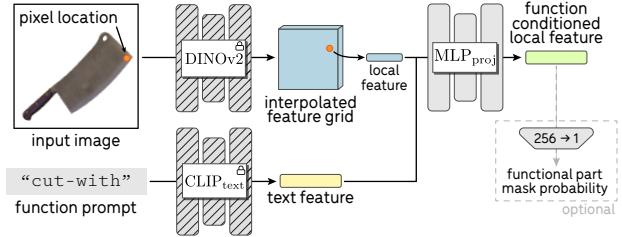


Figure 4. **Local Functional Feature Extraction.** To obtain dense functionally conditioned features, we apply an MLP on top of a function text embedding and the spatial DINO features. The MLP is trained with both functional and spatial contrastive losses.

tion “pour-with,” the features for the neck of the bottle and the spout of the kettle should be similar. Moreover, the mouth of the bottle and the tip of the kettle spout should be in correspondence, as well as the bottom of the bottle’s neck and the bottom of the kettle’s spout. To achieve this, we train a function-conditioned network on top of frozen DINOv2 [54] and CLIP [59] (illustrated in Figure 4), that is applied at the local feature level. Because of significant developments in object segmentation [30, 33] and our focus on object-level understanding, we assume that the input images consist of segmented objects.

**Function-Conditioned MLP.** Given an image and a function, we first extract the image features from the last three blocks of DINOv2 and the function conditioning from CLIP text embeddings. We average the DINOv2 features from each block using learned weights into a single feature grid, and use bilinear interpolation to obtain a feature vector for each pixel location. Then, we concatenate the image feature with the CLIP embedding of the function and pass it through a 3-layer MLP, which produces the final feature at each pixel location. This network can be thought of as a function-conditioned version of the final projection layer used in contrastive learning [4, 22]. We parameterize our model as  $g_\theta(p|I, \mathcal{F})$ , which outputs the normalized feature of pixel  $p$  on image  $I$  conditioned on the function  $\mathcal{F}$ .

We also investigate the option of adding an extra fully connected layer that maps the output feature vector to a prediction for the functional part mask. This allows us to obtain a binary functional part mask at inference time.

**Functional Part Contrastive Learning.** To distill the knowledge of functional part semantics from the VLM, we use contrastive learning based on the pseudo-labeled functional part masks. The parts from two objects that can be used to perform the same function should share a more similar embedding space. Specifically, given two images,  $I_1$  and  $I_2$  of objects that can perform the same function  $\mathcal{F}$ , let the functional part segments be  $P_1^+$  and  $P_2^+$ . Then, define the rest of the objects’ pixels as  $P_1^-$  and  $P_2^-$ . Learning correspondence requires the pixels in  $P_1^+$  to be similar to the ones in  $P_2^+$  but different from the ones in  $P_2^-$ . In addition, to encourage the model to focus on the functionally relevant

regions of objects, we add a term that pushes the features of  $P_1^-$  away from that of  $P_2^-$ .

Let  $\text{sim}(x, y|I_1, I_2, \mathcal{F}) = g(x|I_1, \mathcal{F}) \cdot g(y|I_2, \mathcal{F})$  represent the feature similarity between pixel  $x$  on image  $I_1$  and pixel  $y$  on image  $I_2$  when conditioned on function  $\mathcal{F}$ . For brevity, we short-hand it to  $\text{sim}(x, y)$  below. The infoNCE loss [74] for the function-part contrastive learning given  $(p_1^+, p_1^-, p_2^+, p_2^-) \in (P_1^+, P_1^-, P_2^+, P_2^-)$  is thus

$$\mathcal{L}_{\text{func}} = -\log \frac{e^{\text{sim}(p_1^+, p_2^+)/\tau}}{e^{\text{sim}(p_1^+, p_2^+)/\tau} + e^{\text{sim}(p_1^+, p_2^-)/\tau} + e^{\text{sim}(p_1^-, p_2^-)/\tau}} \quad (1)$$

for temperature  $\tau$ .

When the model predicts functional part masks, we add a binary cross-entropy loss  $\mathcal{L}_{\text{mask}}$  to compare the predicted mask with the pseudo-labeled functional part segment.

**Part Structure via Multi-view Contrastive Learning.** If we train the embedding with only the functional part contrastive loss, we inevitably run into mode collapse issues. That is, the whole spout of the kettle would have the same features regardless of the pixel’s spatial location. To preserve the structural information, we apply dense contrastive learning from multi-view correspondences.

Given two views of an object, we can find corresponding pixels that project to the same location in 3D space. We require a view-invariant feature embedding – a pixel should have high similarity with its corresponding pixel on the other image but remain different from all the other pixels. This encourages the model to learn the structural information of the object, to not collapse the embedding space, and to encode the object part consistently across different views. This multi-view contrastive objective only applies to two images of the same asset. However, because the underlying DINOv2 embedding space enables generalization for visually similar regions, the trained feature embedding can retain information about the structural similarities between functional parts *across* categories.

Formally, let  $q$  be a pixel in the first view  $I$ ,  $q'_+$  be a pixel in the second view  $I'$  that corresponds to the same location in 3D as  $q$ , and any other pixel on  $I'$  be denoted as  $q'_-$ . The multiview contrastive objective is

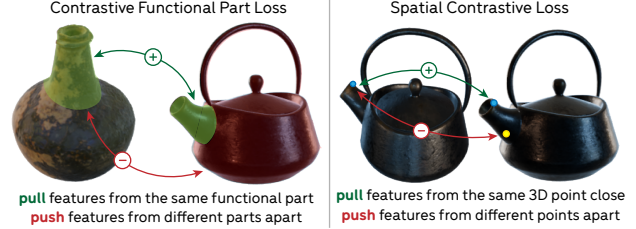
$$\mathcal{L}_{\text{spatial}} = -\log \frac{e^{\text{sim}(q, q'_+)/\tau}}{e^{\text{sim}(q, q'_+)/\tau} + e^{\text{sim}(q, q'_-)/\tau}} \quad (2)$$

Combining the terms, we obtain the final loss

$$\mathcal{L} = \mathcal{L}_{\text{func}} + \lambda_{\text{spatial}} \mathcal{L}_{\text{spatial}} + \lambda_{\text{mask}} \mathcal{L}_{\text{mask}} \quad (3)$$

### 4.3. Implementation Details

We use DINOv2-B as the backbone and an image size of 224. The MLP projector has 3 layers with 1024 hidden dimensions each. We use the Adam [32] optimizer with



**Figure 5. Training Objectives.** To ensure functional part similarity in the learned feature space, we use a part-level contrastive objective to distill *functional part semantics* from VLMs (left). The *spatial* contrastive loss (right) serves a complementary role and prevents the model from collapsing predictions for different regions of a part, e.g., the top and bottom of a kettle spout.

default hyperparameters, a batch size of 50 image pairs, 128 positive and negative sampled points on each image, and a learning rate of  $1 \times 10^{-4}$ . In addition, we use a weight of  $\lambda_{\text{spatial}} = 10$  for the spatial loss and a weight of  $\lambda_{\text{mask}} = 1$  for the mask loss. We use random-color background augmentation during training following [17]. A sensitivity analysis of loss weights and a breakdown of computational costs are provided in the Supplement.

## 5. Experiments

In this section, we benchmark our approach in Sec. 4 and several baseline solutions on the dense functional correspondence task. Since our problem formulation in Sec. 3.1 requires a function as input and focuses on matches within functional parts, it differs significantly from existing benchmarks on semantic correspondence [47, 66]. As such, we leverage the evaluation datasets from Sec. 3.2.

### 5.1. Metrics

We evaluate dense functional correspondence from two different aspects: *correspondence label transfer*, which assesses the precision with which the model can transfer one functional part to another, and *correspondence discovery*, which assesses the model’s ability to identify relevant functional correspondences without any reference input labels.

**Correspondence Label Transfer.** To evaluate the precision of the correspondences that can be found using the learned features, we use normalized pixel distance (Normalized Dist) and percentage of correct keypoints (PCK).

Specifically, let the ground-truth correspondences between images  $I_1, I_2$  given the function  $\mathcal{F}$  be  $\{p_1^1, p_1^2, \dots, p_1^k\}, \{p_2^1, p_2^2, \dots, p_2^k\}$ . For each pixel  $p_1^i$  on image  $I_1$ , we can find its most similar match  $p_2^{j(i)}$  on  $I_2$  using feature similarity. The normalized distance metric is simply the mean of  $\|p_2^{j(i)} - p_1^i\|_2$  normalized by the image size, and PCK@k pixels is the mean of  $\mathbb{1}_{\|p_2^{j(i)} - p_1^i\|_2 < k}$ .

**Correspondence Discovery.** In addition to label transfer, models should discover the relevant set of functional correspondences on its own, without assuming a priori that the

Model	Correspondence Label Transfer			Correspondence Discovery			
	Normalized Dist (↓)	PCK@23p (↑)	PCK@10p (↑)	Best F1@23p (↑)	Best F1@10p (↑)	AP@23p (↑)	AP@10p (↑)
<i>Synthetic Evaluation Dataset</i>							
Chance	0.310	0.165	0.046	0.416	0.176	0.256	0.093
DINO [54]	0.212	0.381	0.148	0.578	0.281	0.381	0.130
SD [87]	0.268	0.298	0.126	0.479	0.231	0.267	0.097
SD-DINO [87]	0.227	0.376	0.161	0.563	0.301	0.341	0.144
CogVLM [78] + DINO	0.180	0.416	0.158	0.678	0.333	0.556	0.188
ManipVQA-P [24] + DINO	0.223	0.346	0.130	0.575	0.269	0.418	0.134
ManipVQA-F [24] + DINO	0.272	0.259	0.093	0.528	0.244	0.320	0.097
Ours (functional only)	0.228	0.287	0.094	0.575	0.233	0.441	0.112
Ours (spatial only)	0.204	0.470	0.227	0.610	0.369	0.412	0.211
Ours (full without mask loss)	<b>0.170</b>	<b>0.486</b>	<b>0.227</b>	<u>0.768</u>	<u>0.470</u>	<b>0.685</b>	<b>0.338</b>
Ours (full with mask loss)	<u>0.172</u>	<u>0.480</u>	0.223	<b>0.774</b>	<b>0.471</b>	<u>0.684</u>	<u>0.330</u>
<i>Real Evaluation Dataset</i>							
Chance	0.313	0.170	0.045	0.417	0.167	0.248	0.087
DINO [54]	0.206	0.408	0.159	0.589	0.294	0.382	0.138
SD [87]	0.259	0.309	0.127	0.503	0.238	0.285	0.101
SD-DINO [87]	0.220	0.385	0.163	0.577	0.301	0.343	0.142
CogVLM [78] + DINO	0.172	0.440	0.169	0.695	0.350	0.561	0.198
ManipVQA-P [24] + DINO	0.204	0.398	0.153	0.600	0.295	0.420	0.148
ManipVQA-F [24] + DINO	0.256	0.309	0.114	0.575	0.281	0.368	0.126
Ours (functional only)	0.200	0.336	0.115	0.652	0.283	0.532	0.148
Ours (spatial only)	0.203	0.472	0.228	0.708	0.353	0.382	0.182
Ours (full without mask loss)	<b>0.152</b>	<b>0.516</b>	<b>0.249</b>	<u>0.775</u>	<u>0.476</u>	<u>0.691</u>	<u>0.344</u>
Ours (full with mask loss)	<u>0.153</u>	<u>0.501</u>	<u>0.235</u>	<b>0.808</b>	<b>0.502</b>	<b>0.730</b>	<b>0.360</b>

Table 1. **Quantitative Evaluation** on the synthetic and real evaluation datasets. The simplest baselines, self-supervised features from Stable Diffusion and DINOv2, perform relatively poorly. Adding semantic knowledge from predicted functional part labels from VLMs can offer slight improvement. Our approach, combining the strengths of both self-supervised features and VLMs, achieves the best performance.

relevant pixels on one image have been given. This capability is essential for potential downstream applications such as object alignment in robot object manipulation.

First, since we assume that the input images are segmented, let  $M_1, M_2$  be the object masks for images  $I_1, I_2$ . For every pixel  $p_1^i \in M_1$ , we find its most similar match  $p_2^{j(i)}$  on  $I_2$  and find the backward match of  $p_2^{j(i)}$  on  $I_1$ , denoted as  $q_1^i$ . As such,  $\|p_1^i - q_1^i\|_2$  captures the level of cycle-consistency of the match. We therefore construct a score  $s = (1 - \|p_1^i - q_1^i\|_2) \cdot \text{sim}(p_1^i, p_2^{j(i)})$  to rank each pair of  $(p_1^i, p_2^{j(i)})$ , using both similarity and cycle consistency.

Then, we consider the top  $t\%$  of all pairs as “discovered” and compare them with the ground-truth. A discovered pair  $(x_1, x_2)$  is equivalent to a ground-truth pair  $(y_1, y_2)$  if both end points are within  $k$  pixels of the ground truth. Increasing  $t$  results in higher recall but potentially lower precision: the number of discovered ground-truth correspondences monotonically increases while the percentage of correct correspondence tends to decrease. Sweeping  $t$  produces a precision-recall curve, from which we can calculate the best F1 score (at  $k$  pixels) and the average precision (AP) (at  $k$  pixels). Formally,  $\text{Best F1} = \max_t \frac{2 \times \text{Precision}_t \times \text{Recall}_t}{\text{Precision}_t + \text{Recall}_t}$  and  $\text{AP} = \sum_t (\text{Recall}_t - \text{Recall}_{t-1}) \text{Precision}_t$ .

## 5.2. Baselines

We describe several baseline methods below.

**Self-Supervised Features.** Powerful correspondences emerge in the feature space of large pre-trained vision foundation models, as reviewed in Sec. 2. We use features extracted from DINOv2 [54], Stable Diffusion [62, 87], and fused features of the two [87] as baselines. We use feature-level similarity between pixel pairs to find correspondences.

**Self-Supervised Features and VLM Grounding.** Since our task requires both semantic and structural reasoning based on the function prompt, these baselines chain a VLM that grounds functional parts with a pre-trained model that provides structural priors. Given an image pair, we use functional part bounding boxes generated by the VLM for each image, and then use self-supervised features to find correspondences within these part labels. This approach can benefit both label transfer and discovery because the functional part prediction adds a constraint on the space of possible matches, making it easier to find accurate matches. We consider two VLMs as the functional part grounding modules to be combined with off-the-shelf DINOv2 features:

- CogVLM [78], which outputs bounding boxes based on prompts of the functional part.

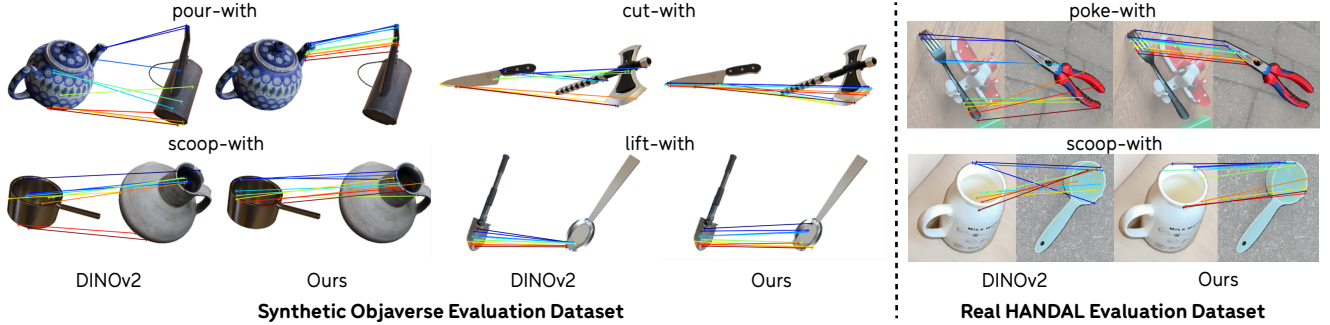


Figure 6. **Correspondence Discovery Comparisons.** We observe that our approach more reliably retrieves the functionally relevant correspondences than off-the-shelf DINOv2. The top 10 highest-ranked matches are shown.

- ManipVQA [24], an affordance-grounding model that outputs bounding boxes conditioned on actions. We use the 7B model in our experiments. We also prompt ManipVQA in two ways, one with the functional part name and the other with the function itself because the model is finetuned for robotic tasks. We refer to these as ManipVQA-P and ManipVQA-F, respectively.

### 5.3. Quantitative Comparisons

Results in Table 1 evaluate the performance of our method and baseline solutions on the synthetic and real evaluation datasets introduced in Sec. 3.2. Results show that our model trained on fully synthetic data can generalize to real images.

Compared to baseline solutions that solely use self-supervised features, our full model – trained with both functional and spatial contrastive loss – consistently outperforms. These metrics demonstrate that the pseudo-label quality is sufficient for learning meaningful functional correspondences. Additionally, given that the evaluation dataset predominantly includes cross-category pairs, Table 1 illustrates that self-supervised features struggle with cross-category generalization. Further evidence is provided in the Supplement, where we present a detailed breakdown of metrics for both within- and across-category pairs.

Compared to baselines using VLM grounding, even with CogVLM bounding boxes as additional functional part information, off-the-shelf DINOv2 features underperform relative to our full model. The margin is generally smaller, which highlights the importance of understanding the context of the function. On the other hand, ManipVQA outputs less accurate bounding boxes, which is reflected in the metrics. In particular, prompting with the part instead of the function is significantly better, which shows the difficulty of zero-shot affordance grounding given a function name. Note also that running CogVLM inference is roughly 50 times slower than our model and running ManipVQA inference is roughly 1000 times slower than our model.

**Ablations.** We ablate the role of the functional and spatial contrastive loss in Table 1. The model trained solely with functional loss performs poorly in both label transfer and

correspondence discovery. The model trained solely with spatial loss is better but still falls short compared to the full model due to its lack of functional information. Finally, models with and without mask loss share similar performances. The model with mask loss does outperform the model without it in all metrics for correspondence discovery on the real evaluation dataset, which represents the least constrained and most realistic case. This optional mask prediction module can learn functional part masks with minimal additional cost.

### 5.4. Qualitative Results

We present results for correspondence label transfer in Figure 1 and correspondence discovery in Figure 6. Our model predictions not only capture object parts specific to the input function, but also preserve the structural relation among parts. Figure 6 shows top 10 matches according to the score from Section 5.1 separated by 5 pixels each. DINOv2 features are not function-aware and result in inaccurate matching, especially in cross-category image pairs. In comparison, our model produces dense matches between functional parts from different object categories with high spatial precision, *e.g.*, matching the rim of a saucepan with the rim of a jug. Overall, our model demonstrates a deep understanding of functional and structural information of objects, which produces high-quality dense functional correspondences.

## 6. Conclusion

We have introduced the problem of dense functional correspondence, where input images contain objects with similar functionality but possibly come from distinct object categories. We have proposed a principled approach to obtain dense 2D functional correspondences from 3D object alignments and curated datasets for comprehensive evaluations. To tackle the task, we have presented a weakly-supervised framework that distills semantic information from vision-language models, while learning structural information through tuning self-supervised features with a multi-view contrastive loss. Our model outperforms a set of baselines in both synthetic and real-world benchmarks.

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