Agile Modeling: From Concept to Classifier in Minutes

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Abstract

The application of computer vision methods to nuanced, subjective concepts is growing. While crowdsourcing has served the vision community well for most objective tasks (such as labeling a "zebra"), it now falters on tasks where there is substantial subjectivity in the concept (such as identifying "gourmet tuna"). However, empowering any user to develop a classifier for their concept is technically difficult: users are neither machine learning experts nor have the patience to label thousands of examples. In reaction, we introduce the problem of Agile Modeling: the process of turning any subjective visual concept into a computer vision model through real-time user-in-the-loop interactions. We instantiate an Agile Modeling prototype for image classification and show through a user study (N=14) that users can create classifiers with minimal effort in under 30 minutes. We compare this user driven process with the traditional crowdsourcing paradigm and find that the crowd's notion often differs from that of the user's, especially as the concepts become more subjective. Finally, we scale our experiments with simulations of users training classifiers for ImageNet21k categories to further demonstrate the efficacy of the approach.

Keywords: User-in-the-Loop, Active Learning, Personalization, Neural Networks

1. Introduction

Whose voices, and therefore, whose labels should an image classifier learn from? Today, the answer to this question is often left implicit in the data collection process. Concepts are defined by researchers before curating a dataset [13]. Decisions for which images constitute positive versus negative instances are conducted by crowd workers rating this predefined set of categories [27, 52]. A model is then trained on the aggregated ground truth, learning to predict the crowd's consensus.

Figure 1: Visual concepts can be subjective. For example, a graduate student may think that a well-prepared tuna sandwich is considered `gourmet tuna`, but a trained chef might disagree.

As computer vision matures, its application to nuanced, subjective use cases is burgeoning. While crowdsourcing has worked well for objective tasks (e.g., identifying ImageNet [13] concepts like "zebra"), it now falters on tasks where there is substantial subjectivity [17]. For example, in Figure 1, a sushi chef might covet a classifier to source gourmet tuna for inspiration. Majority vote by crowd workers may not converge to the same definition of what makes a tuna dish gourmet. This point is also supported by our experiments.

This paper highlights the need for user-centric approaches to developing real-world classifiers for these subjective concepts. To define this problem space, we recognize the following challenges.

*. Equal contribution.

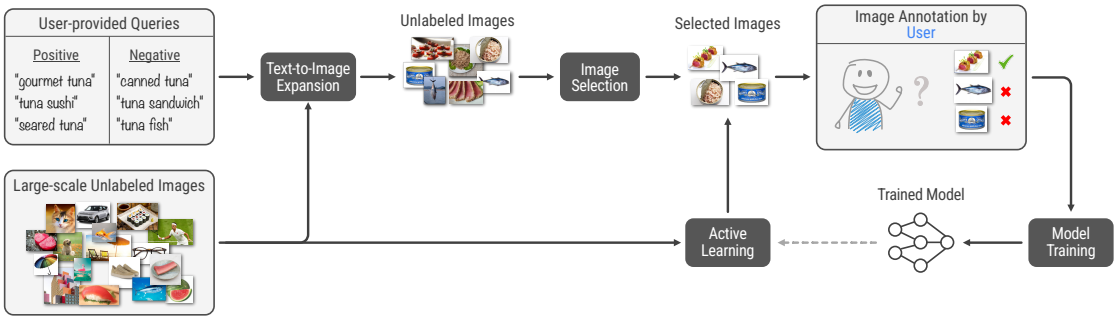


Figure 2: Overview of the Agile Modeling framework.

First, subjective concepts require users to participate in the data curation process. Second, users are usually not machine learning experts, so we need interactive systems that elicit the subjective decision boundary from the user. Third, users don't have the time and patience to sift through the thousands of training instances that is typical for most image classification datasets [13, 30, 24].

To tackle these challenges, we introduce the problem of **Agile Modeling**: the process of turning any visual concept into a computer vision model through a real-time user-in-the-loop process. Just as software engineering matured from prescribed procedure to "agile" software packages augmenting millions of people to become software engineers, Agile Modeling aims to empower anyone to create personal, subjective vision models. It formalizes the process by which a user can initialize and interactively guide the training process while minimizing the time and effort required to obtain a model. With the emergent few-shot learning capabilities of vision foundation models [41, 19], now is the right time to begin formalizing and developing Agile Modeling systems.

We instantiate an Agile Modeling prototype for image classification to highlight the importance of involving the user-in-the-loop when developing subjective classifiers. Our prototype allows users to bootstrap the learning process with a single language description of their concept (e.g., "gourmet tuna") by leveraging vision-language foundation models [41, 19]. Next, our prototype uses active learning to identify instances which, if labeled, would maximally improve the classifier. These few instances are surfaced to the user, who is only asked to identify which instances are positive—something they can do without a background in machine learning. This iterative process continues with more active learning steps until the user is satisfied with their classifier's performance.

Our contributions are:

1) We formulate the Agile Modeling problem, where users have a central role in model creation.
2) We demonstrate how to build a real-time prototype by leveraging SOTA image-text co-embeddings for fast image retrieval and model training. Each round of active learning takes a few minutes on a single desktop CPU. In under 5 minutes, user-created models outperform zero-shot classifiers.
3) In a setting resembling real-world conditions, we compare models trained with labels from real users versus crowd raters. The value of user-labeled data increases when the concept is nuanced.
4) We verify these results with a simulated experiment of 100 concepts from ImageNet21k.
5) We open source the implementation of our Agile Modeling prototype on our GitHub page [53], enabling anyone to create classifiers for their concepts.
6) We release all annotations labeled in our user study for 14 novel concepts, enabling researchers to experiment with the concepts defined by our users [53].

2. Related work

Our work is related to human-in-the-loop, personalization, few-shot, and active learning. Due to space constraints, we include an ample discussion in Appendix A, and provide a summary here.

The most relevant related work comes from the systems community [38, 42, 58, 33], where systems such as Tropel [38] and Snorkel [42, 58] have been created to automate and scale data

annotation. However, these systems are insufficient for conveying the meaning of nuanced, subjective concepts to crowd workers or via labeling functions. The closest work to ours is [33], which proposes a method of interleaving model training and labeling to build classifiers for rare concepts. However, our work differs in several ways: (1) our method allows users to express concepts in natural language, (2) we use concepts proposed by real users rather than existing benchmarks, (3) our system works in real-time on a much larger scale of data.

Our work is also related to personalization in computer vision [21, 7, 16]. However, the settings being tackled in the personalization literature are different than ours, and also do not focus on building real-time systems for user interaction. Our method also includes components that span the areas of zero-shot retrieval, few-shot and active learning. We discuss these in the appendix.

3. Agile Modeling

We consider the scenario where a user comes to the Agile Modeling system with just a subjective concept in mind—in our running example, `gourmet tuna`. First we lay out the high level Agile Modeling framework, and then describe how we instantiate a prototype.

3.1 The framework

As shown in Figure 2, the Agile Modeling framework guides the user through the creation of an image classifier through the following steps:

1. Concept definition. The user describes the concept in text.
2. Text-to-image expansion and image selection. The text is used to mine relevant images from a large unlabeled source of images, for the user to rate.
3. Rating. The user rates the images as positive or negative through a rating tool.
4. Model training. Automatically train a binary classifier with the rated images.
5. Active learning (AL). The initial model can be improved very quickly via one or more rounds of AL, which consists of 3 repeated steps: (1) the framework invokes an algorithm to select from millions of unlabeled images to rate; (2) the user rates these; (3) the system retrains the classifier with all the available labeled data.

The user's input is used for only two types of tasks, which require no machine learning or engineering experience: first in providing the text phrases and second in rating images.

3.2 The prototype

For our prototype, we assume that the user only has access to a large, unlabeled dataset of images, which is something that is easily available through the Internet [41]. Our aim is to select and label a small subset of this large dataset and use it as training data.

Concept definition. Users initiate the Agile Modeling process by expressing their concept in words. Through our interactions with users, we find that expressing the concept in terms of both positive and negative phrases is an effective way of mining positive and hard negative examples for training. The positive phrases allow the user to express both the concept as a whole (e.g., `gourmet tuna`) and specific visual modes of it (e.g., `tuna sushi`). The negative phrases are important in finding negative examples that could be easily confused (e.g., `canned tuna`).

Text-to-image expansion and image selection. The phrases provided by the user are used to identify a first set of relevant training images. We leverage recent, powerful image-text models, such as CLIP [41] and ALIGN [19], and co-embed both the unlabeled data and the text phrases into the same space. We then run a nearest-neighbors search to retrieve 100 images nearest to each text embedding, using a fast nearest-neighbors implementation [60, 18]. From the set of all neighbors, we randomly sample 100 images for the user to rate, for both positive and negative phrases.

Data labeling by user. The selected images are shown to the user for labeling. We created a simple user interface where the user is shown one image at a time and is asked to select whether it is `positive` or `negative`. The median time it took to rate a single image by the participants in our user study was 1.7 ± 0.5 seconds (details in Section 4). Since users rate 100 images / round, they spend ∼3 minutes before a new model is trained.

Model training. We train our binary image classifier using all previously labeled data. This setup is challenging because there is little data available to train a generalizable model, and the entire training process must be fast to enable real-time engagement with the user waiting for the next phase of images. While the study of real-time few-shot methods is an interesting problem for future instantiations of Agile Modeling, we adopted another solution: we again take advantage of powerful pretrained models like CLIP and ALIGN to train a small multilayer perceptron (MLP), with only 1-3 layers, on top of image embeddings provided by such large pretrained models.

Active learning (AL). When selecting samples to rate, state-of-the-art AL methods generally optimize for improving the model fastest [43]. However, when the user is the rater, we have a real-time constraint to minimize the user-perceived latency. Therefore, AL methods that rely on heavy optimization strategies cannot be used here. In our solution, we adopt a well-known and fast method called *uncertainty sampling* or *margin sampling* [10, 46, 29]. We also considered the approach adopted by [33], which is a combination of margin and positive mining. We compared both margin and this approach in our experiments. We run one or more rounds of AL, the number of rounds is determined by the time the user has.

We release a Colab implementation of this prototype at our GitHub page [53].

4. Experiments with real users

We run user studies with real users in the loop, and show that: **(1)** In only 5 minutes, the performance of an Agile model can exceed that of state-of-the-art zero-shot models based on CLIP and ALIGN by at least 3% AUC PR (Section 4.3.1); **(2)** For hard, nuanced concepts, Agile models trained with user annotations outperform those trained with crowd annotations even when crowd raters annotate 5× more data (Section 4.3.2); **(3)** Smaller active learning batch sizes perform better than larger ones, but there is an efficiency trade-off (Appendix D.4); **(4)** Agile models using ALIGN embeddings outperform does using CLIP throughout model iterations (Section 4.3).

4.1 Choosing subjective concepts

Concepts. For our user studies we select a list of 14 novel concepts, spanning different degrees of ambiguity and difficulty, curated by surveying real-world practitioners for suggestions. The list ranges from more objective concepts such as `pie chart`, `in-ear headphones` or `single sneaker on white background`, to more subjective ones such as `gourmet tuna`, `healthy dish`, or `home fragrance`. The full list of concepts and a measurement on their diversity is included in Appendix B.

Participants & workflow. We sourced 14 volunteer users to interact with our system, each building a different concept. Our participants were adults that spanned a variety of age ranges (18-54), gender identities (male, female), and ethnicities (White, Asian, and Middle Eastern). We provided users with the concept name and a brief description, but allowed them to define the full interpretation. For instance, one of our users, who was provided with the concept `stop-sign`, limited its interpretation to only real-world stop-signs inspired by a self-driving car application: only stop signs in traffic were considered positive, while stop-sign drawings or posters were negative.

Data sources. Our prototype requires an unlabeled source of images from which to source training labels. We use LAION-400M [47], due to its size and diversity. Preprocessing details in Appendix C.

4.2 Experimental setup

Models and training. All models are multilayer perceptrons (MLP) that take image representations from a frozen pretrained model as input and contain one or more hidden layers. All training details, including model size, optimizer, etc., can be found in Appendix I.

Baselines. One baseline we compare against is zero-shot learning, which corresponds to zero effort from the user. We implement a zero-shot baseline that scores an image by the cosine similarity between the image embedding and the text embedding of the desired concept. For evaluation metrics that require binary predictions, we classify an image as positive if the cosine similarity exceeds a certain threshold. We chose the threshold to be 0.28 when using CLIP based on LAION-5B's human inspection [48], and 0.2 when using ALIGN based on our inspection. We also compare with a recently released active learning algorithm for learning rare vision categories [33] described in Section 2. We replace our AL algorithm with theirs and compare the performance in Appendix D.4.

Evaluation. Please see Appendix D for our strategy for building an evaluation set. The final dataset has over 500 images per category with approximately 50% positive rate, rated by the user.

Other hyperparameters. The text-to-image expansion expands each user-provided query to 100 nearest-neighbor images. Next, the image selection stage randomly selects a total of 100 images from all queries, leading to an initial training set of 100 samples for the first model. Users are asked to perform 5 rounds of active learning, rating 100 images per step. These hyperparameters were chosen based on two held-out concepts, and the ablation results in Appendix D.4.

4.3 Results

4.3.1 Users produce classifiers in minutes

A key value proposition of Agile Modeling is that the user should be able to train a model in minutes. We now report the feasibility of this proposition.

Measuring Time. The time per step of the framework is detailed in Table 1. Our Agile Modeling implementation trains one initial model and conducts 5 AL rounds, taking 24 minutes on average to generate a final model.

Step	Time
User rates 100 images	2 min 49 s ± 58 s
AL on 10M images	58.6 s ± 0.8 s
Training a new model	23.1 s ± 0.2 s

Table 1: The average and stddev of time per step in our prototype.

Comparison with zero-shot. We start by comparing against zero-shot classification, which corresponds to a scenario with minimal effort from the user. In Figure 3, we present the performance of our Agile Modeling instantiations against a zero-shot baseline across two image-text co-embeddings: CLIP [41] and ALIGN [19]. We find that the zero-shot performance is roughly on par as a supervised model trained on 100 labeled examples by the user. However, after the user spends a few more minutes rating (i.e., as the number of user ratings increases from 100 to 600), the resulting supervised model outperforms zero-shot. We also show results per concept in Appendix D.3.

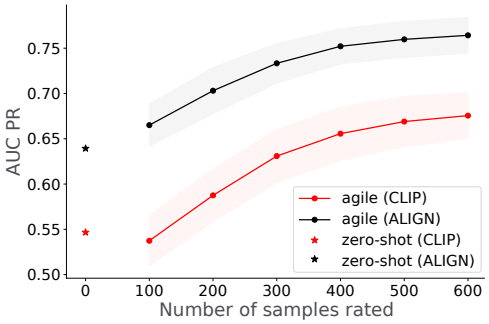
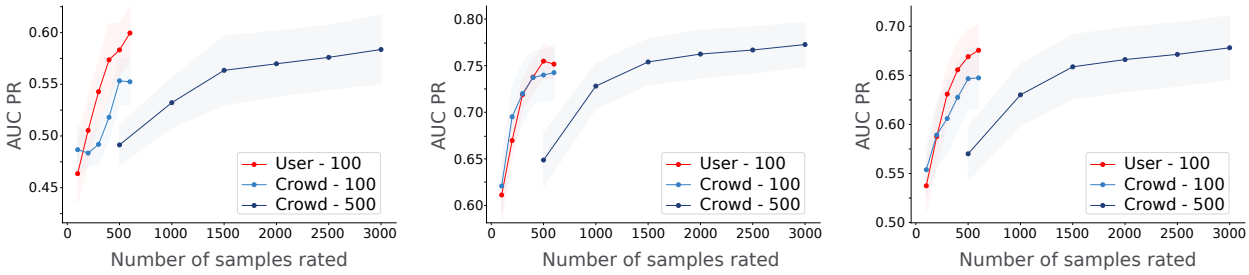


Figure 3: Model AUC PR (mean and stderr over concepts) per amount of samples rated. Each • is an AL round.

User time versus performance. To measure the trade-off between user time versus model performance, we show in Figure 3 the model's AUC PR across AL rounds (more metrics in Appendix E), using both CLIP and ALIGN representations as input to our models. We also compare against the respective zero-shot models, considered the zero effort case. For both representations, we see a steeper performance gain for the first 3 AL rounds, after which the performance starts to



(a) Hard concepts (b) Easy concepts (c) All concepts

Figure 4: Performance per # samples rated by user or crowd. AUC PR mean and stderr over subsets of concepts: hardest (left), easiest (middle), all (right). Each • represents an AL round.

plateau, consistent with existing literature on AL for computer vision [20]. Interestingly, for CLIP, the initial model trained on 100 images performs worse than zero-shot, but it outperforms zero-shot after just one round of AL. We do not see this for ALIGN, where even 100 samples are enough to outperform the zero-shot model. We compare CLIP and ALIGN in more detail in Appendix D.4. Importantly, we show that with only 5 minutes of the user's time (Table 1), we can obtain a model that outperforms the zero-shot baseline by at least 3%. After 24 minutes, the gain grows to 16%.

4.3.2 Value of users in the loop versus crowd workers

We now study the value of empowering users to train models by themselves. We tackle the following question: *Are there concepts for which a user-centered Agile framework leads to better performance?*

Users have an advantage over crowd raters in their ability to rate images according to their subjective specifications. However, this subjectivity varies by concept: if a concept is universally understood, the advantage diminishes. Conversely, complex, nuanced concepts are harder for crowd workers to accurately label. To study this, we partition the concepts into 2 datasets based on their difficulty, using zero-shot performance (Figure 6) as a proxy for concept difficulty. The 7 concepts with the highest zero-shot performance are considered "easy," while the remaining 7 concepts are considered "hard." The grouping can be found in Appendix G. The "difficult" concepts include more subjective concepts such as `gourmet tuna`, or concepts with multiple ambiguous visual modes like `healthy dish`; the "easy" set includes self-explanatory concepts such as `dance` or `single sneaker on white background`. We then evaluate models trained by three sets of raters:

1. `User-100`: Users rate 100 images for the initial model and every AL round (total 600).
2. `Crowd-100`: Crowd workers rate 100 images for the initial model and every AL round (total 600).
3. `Crowd-500`: Crowd workers rate 500 images for initial model and every AL round (total 3000).

The only difference in the configurations above is who the raters are (user or crowd) and the total number of ratings. Crowd workers read instructions created by the users, who noted difficult cases that they found during labeling. Details about the crowd instructions can be found in Appendix H.

The results in Figure 4 show the average performance for the "hard", "easy" and all concepts as a function of the number of rated samples, using CLIP embeddings (per-concept results in Appendix J). On hard concepts, models trained with users (`User-100`) outperform models trained with crowd raters, even when 5× more ratings are obtained from the crowd (`Crowd-500`). This suggests that Agile Modeling is particularly useful for harder, more nuanced and subjective concepts.

5. Discussion & Conclusion

We formalized the *Agile Modeling* problem, empowering users without ML experience to create their own image classifiers. By using the latest advances in image-text pretrained models, we were able to initialize, train, and perform active learning in just a few minutes, enabling real-time user interaction for rapid model creation in less than 30 minutes. We also confirmed that our framework can be effectively applied across a larger number of concepts on ImageNet21k (Appendix F).

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Appendix A. Detailed Related Work

We expand our discussion on related work on human-in-the-loop computation, personalized computer vision, and zero and few-shot learning.

Building models with humans-in-the-loop. Involving humans in the training process has a long history in crowdsourcing [14, 1, 37, 15], developmental robotics [54, 23, 31], and computer vision [26, 11, 61, 25, 36]; and has recently also grown in popularity in large language modeling [35]. However, these methods are primarily focused on improving model behavior. In other words, they ask "how can we leverage human feedback or interactions to make a better model?" In comparison, we take a user-centric approach and ask "how can we design a system that can empower users to develop models that reflect their needs?"

With this framing in mind, our closest related work comes from the systems community [38, 42, 58, 33]. Tropel [38] automated the process of large-scale annotation by having users provide a single positive example, and asking the crowd to determine whether other images are similar to it. Nevertheless, for xsubjective concepts a single image may be insufficient to convey the meaning of the concept to the crowd. Others such as Snorkel [42, 58] use expert-designed labeling functions to automatically annotate a large, unlabeled dataset. However, large datasets of images contain metadata that is independent of the semantics captured within the photo [55]. With the recent emergent few-shot capabilities in large vision models, it is now time to tackle the human-in-the-loop challenges through a modeling lens appropriate for the computer vision community. Our prototype can train a model using active learning on millions of images on a single CPU in a matter of minutes. Perhaps the closest work to ours is [33], which proposes a method of interleaving model training and labeling phases to build classifiers for rare concepts. However, our work differs in several ways: (1) our method obviates the requirement of having a few positive images by allowing users to find them quickly with natural language, (2) we use concepts proposed by real users, rather than using concepts from existing benchmarks, and (3) we demonstrate that our system works in real-time on a much larger scale of data: our method can train a model and run active learning on millions of images on a single CPU in a few minutes, which is much faster than [33]'s end-to-end training of a ResNet.

Personalization. Although personalization [21, 7, 16] is an existing topic in building classification, detection, and image synthesis, the settings being tackled are different than ours. For example, in [7] personalized concepts refer to objective instance-specific concepts (e.g. "my dog"), and the user must provide a few images to begin. [16] tackles the problem of personalized text-to-image generation. [21] assumes the training images are either given in one go (few-shot) or in a continual learning fashion, and their method has no control over data selection. Most importantly, existing work in this area usually tests their resultant models on standard vision datasets and does not build real-time systems that can enable the user to select the few-shots and later improve the model with active learning, while we run a study with real users, focus on real-world sized datasets and on new, subjective concepts.

Zero and few-shot learning. Since users have a limited patience for labeling, Agile Modeling aims to minimize the amount of labeling required, opting for few-shot solutions [57, 59, 51, 4, 34]. Luckily, with the recent few-shot properties in vision-language models—found for example in CLIP [41] and ALIGN [19]—it is now possible to bootstrap classifiers with language descriptions [40]. Besides functioning as a baseline, good representations have shown to similarly bootstrap active learning [56]. We demonstrate that a few minutes of annotation by users can lead to sizeable gains over these zero-shot classifiers.

Real-time active learning. Usually few-shot learning can only get you so far, especially for subjective concepts where a single language description or a single prototype is unlikely to cap-

ture the variance in the concept. Therefore, iterative approaches like active learning provide an appropriate formalism to maximize information about the concept while minimizing the amount of labels needed [50, 5]. Active learning methods derive their name by "actively" asking users to annotate data which the model currently finds most uncertain [28] or believes is most representative of the unlabeled set [49] or both [2, 6]. Unfortunately, most of these methods require expensive pre-processing, reducing their utility in most real-world applications [12]. Methods to speed up active learning limit the search for informative data points [9] or use low-performing proxy models for data selection [8] or use heuristics [49, 39]. We show that performing model updates and ranking images on cached co-embedding features is a scalable and effective way to conduct active learning.

Appendix B. Concepts

We provide the full list of concepts, along with the text phrases provided by the users. Each concept name was automatically added to the list of positive text phrases.

1. `gourmet tuna`
   (a) Positive text phrases: tuna sushi, seared tuna, tuna sashimi
   (b) Negative text phrases: canned tuna, tuna sandwich, tuna fish, tuna fishing
2. `emergency service`
   (a) Positive text phrases: firefighting, paramedic, ambulance, disaster worker, search and rescue
   (b) Negative text phrases: construction, crossing guard, military
3. `healthy dish`
   (a) Positive text phrases: salad, fish dish, vegetables, healthy food
   (b) Negative text phrases: fast food, fried food, sugary food, fatty food
4. `in-ear headphones`
   (a) Positive text phrases: in-ear headphones, airpods, earbuds
   (b) Negative text phrases: earrings, bone headphones, over-ear headphones
5. `hair coloring`
   (a) Positive text phrases: hair coloring service, hair coloring before and after
   (b) Negative text phrases: hair coloring product
6. `arts and crafts`
   (a) Positive text phrases: kids crafts, scrapbooking, hand made decorations
   (b) Negative text phrases: museum art, professional painting, sculptures
7. `home fragrance`
   (a) Positive text phrases: home fragrance flickr, scented candles, air freshener, air freshener flickr, room fragrance, room fragrance flickr, scent sachet, potpourri, potpourri flickr
   (b) Negative text phrases: birthday candles, birthday candles flickr, religious candles, religious candles flickr, car freshener, car freshener flickr, perfume, perfume flickr
8. `single sneaker on white background`
   (a) Positive text phrases: one sneaker on white background
   (b) Negative text phrases: two sneakers on white background, leather shoe

9. `dance`
   (a) Positive text phrases: ballet, tango, ballroom dancing, classical dancing, professional dance
   (b) Negative text phrases: sports, fitness, zumba, ice skating
10. `hand pointing`
   (a) Positive text phrases: hand pointing, meeting with pointing hand, cartoon hand pointing, pointing at screen
   (b) Negative text phrases: thumbs up, finger gesture, hands, sign language
11. `astronaut`
   (a) Positive text phrases: female astronaut, spacecraft crew, space traveler
   (b) Negative text phrases: spacecraft, space warrior, scuba diver
12. `stop sign`
   (a) Positive text phrases: stop sign in traffic, stop sign held by a construction worker, stop sign on a bus, stop sign on the road, outdoor stop sign, stop sign in the wild
   (b) Negative text phrases: indoor stop sign, slow sign, traffic light sign, stop sign on a poster, stop sign on the wall, cartoon stop sign, stop sign only
13. `pie chart`
   (a) Positive text phrases: pie-chart
   (b) Negative text phrases: pie, bar chart, plot
14. `block tower`
   (a) Positive text phrases: toy tower
   (b) Negative text phrases: tower block, building

Our concepts cover a large spread over the visual space, measured using the average pairwise cosine distance between the concept text CLIP embeddings. For our 14 concepts, the average pairwise cosine distance was 0.73 ± 0.13. In comparison, ImageNet's average pairwise cosine distance was 0.35 ± 0.11.

Appendix C. Experimental details

Data sources. Since our prototype requires an unlabeled source of images from which to source training labels, we use the LAION-400M dataset [47], due to its size and diversity. We discard the text associated with the images, remove duplicate URLs, and split the images into a 100M training and 100M testing images. All trained Agile models use data exclusively from the unlabeled training split, including during nearest neighbor search, active learning, and training. For evaluation, we only use data from the 100M test set, where each concept's evaluation set consists of a subset of this data rated by the user.

Appendix D. Evaluation strategy

To evaluate the models trained with the Agile Modeling prototype, we require an appropriate test set. Ideally, the user would provide a comprehensive test set—for example, ImageNet holds out a test set from their collected data [44]. However, since our users are volunteers with limited annotation time, they cannot feasibly label the entire LAION-400M dataset or its 100M test split.

Additionally, since we are considering rare concepts, labeling a random subset of unlabeled images is unlikely to yield enough positives.

To address these problems, we considered multiple evaluation strategies, all discussed in detail below. To summarize our final evaluation strategy choice, we ran stratified sampling on each evaluated model, which divides images based on their model score into 10 strata ranging from $[0, 0.1)$ to $[0.9, 1.0]$. In each strata, we hash each image URL to a 64-bit integer using the pseudorandom function SipHash [3] and include the 20 images with the lowest hashes in the evaluation set. Each model contributes equally to final test set. The final evaluation set has over 500 images per category with approximately 50% positive rate.

D.1 Proposed evaluation strategies

We considered the following strategies for evaluation:

Labeling the entire unlabeled set. The most accurate evaluation metric is to label the entire unlabeled set. However, this is infeasible, as the user would have to label hundreds of millions of images.

Random sampling from unlabeled set. To reduce the number of images to label, we could randomly sample until we hit a desired amount. However, since most of the concepts are rare ($< 0.1\%$ of the total amount of data), this means our evaluation set would have very few positives.

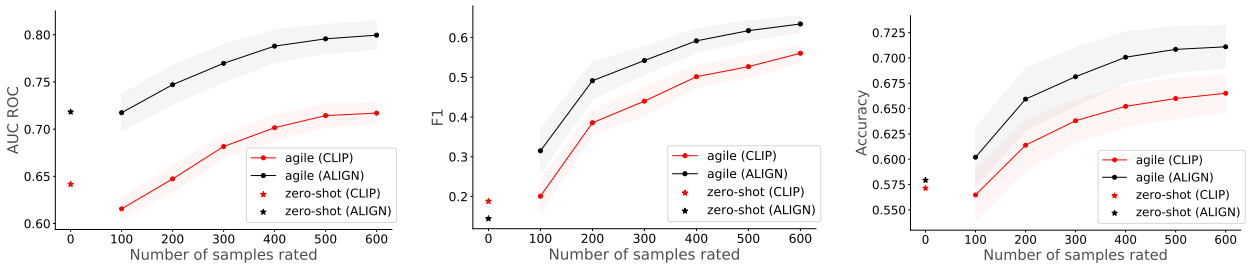
Holdout of training data. As the user labels new ground truth, hold out a fraction of it for evaluation. The benefit is that the user does not have to label any extra data. The main detriment is that the evaluation set comes from the exact same distribution as the training set, leading to overestimates of performance, as there are no new visual modes in the evaluation set.

Random sampling at fixed prediction frequencies. Choose a set of operating points. For each operating point randomly sample K images with score higher than that operating point. The operating points can be selected as the model prediction frequency—for example, we can calculate precision of the highest confidence 100, 1000, and 10000 predictions. The metric that will be directly comparable across models is precision vs prediction frequency. To minimize rating cost we can use the deterministic hash approach. The main problem is that the choice of operating points varies depending on the particular class. Classes that are rare or harder to correctly predict may need stricter operating points than common and easy classes. Furthermore, with this approach we cannot compute a PR curve, just some metrics at specific operating points.

Stratified sampling without weights [our chosen approach]. Collect new evaluation images by (1) calculating model scores, (2) bucketing the images by model score (e.g., [0, 0.1), [0.1, 0.2),..., [0.8, 0.9), [0.9, 1]), (3) rating k examples per bucket. To minimize any bias towards any particular model, we can repeat this process to retrieve an evaluation set per model and merge to get the final evaluation set. Additionally, we can use a deterministic hash instead of random sampling to encourage high overlap across the images chosen to save on the total rating budget. The major upside is that, using a small number of images rated, we can get a relatively balanced dataset of positives and negatives, while also mining for hard examples to stress test the models. The main limitations of this method are:

1. Stratified sampling requires good bucket boundaries to work well, which is not guaranteed.

2. The metric will be biased since samples selected from buckets with a smaller number of candidates (such as the [0.9, 1] bucket) will have more influence than samples from buckets with lots of candidates (e.g., the [0, 0.1) bucket).



(a) AUC ROC. (b) F1 score. (c) Accuracy.

Figure 5: Model performance per amount of samples rated by the user. Mean and standard error over all concepts, for multiple metrics.

3. Merging image sets from multiple models may bias towards the models make common predictions. However, we hope that pseudorandom hashing selects the same images and prevents this from occurring.

Stratified sampling with weights. This involves the same process as stratified sampling without weights, but whenever computing a metric, you weigh the sample by the distribution of scores it came from. This unbiases sampling from each strata, but for very large buckets (e.g., the [0, 0.1) bucket), the weight would be extremely large. This means that predicting incorrectly on any of these images overpowers all correct predictions on other buckets.

Based on the pros and cons of all these approaches, we chose *stratified sampling without weights* for our experiments, which we believe is most representative for our problem setting.

D.2 Evaluation set statistics

In Table 2, we show that our stratified sampling method chooses a tractable number of images to rate, while keeping the positive and negative count relatively balanced.

Concept Name	# Images	Pos. Rate
arts and crafts	707	0.66
astronaut	637	0.36
block tower	669	0.36
dance	730	0.47
emergency service	675	0.50
gourmet tuna	576	0.27
hair-coloring	645	0.67
hand-pointing	832	0.34
healthy dish	633	0.36
home-fragrance	716	0.39
in-ear-headphones	687	0.42
pie-chart	594	0.42
single sneaker on white background	556	0.49
stop sign	704	0.44

Table 2: Statistics showing the total number of images and the positive rate in each concept's evaluation set.

D.3 Additional results

We also include per-concept results for the experiment discussed in Section 4.3. Figure 6 shows the AUC PR of models trained with our Agile Modeling prototype using CLIP and ALIGN embeddings, respectively, for each of the 14 concepts. We also report the corresponding zero-shot model performance.

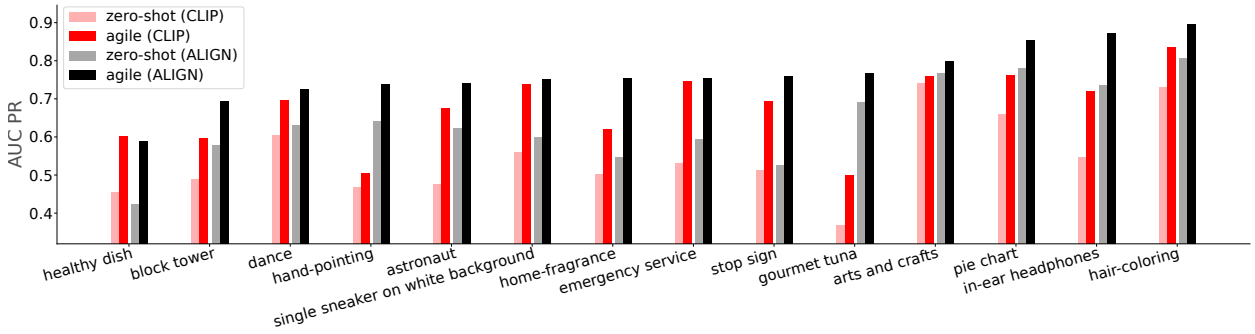


Figure 6: Performance per concept for zero-shot and Agile models on CLIP and ALIGN embeddings.

D.4 Ablation studies

Although our main contribution is introducing the problem of Agile Modeling, instantiating our prototype explores a number of design decisions. In this section, we lay out how these designs change the outcome.

Active learning method. Throughout the paper, we instantiate the active learning component with the well-known margin sampling method [45]. We now compare it to the active learning method used in Mullapudi et al [33]. We ran a version of our instantiation of the Agile framework where we replace margin with the combined margin and positive mining strategy chosen by [33] and described in Section 3.2. The performance of the two methods per AL round is shown in Figure 7. Interestingly, despite the fact that Mullapudi et al. [33] introduced this hybrid approach to improve upon margin sampling, in this setting the two methods perform similarly across all AL rounds. We see the same effect on most concepts when inspecting on a per-concept basis in Appendix E.2. One potential explanation for this is that the initial model trained before AL is already good enough (perhaps due to the powerful CLIP embeddings) for margin sampling to produce a dataset balanced in terms of positive and negative, and thus explicitly mining easy positives as in [33] is not particularly useful. Since the two methods perform equivalently, we opted for the simpler and more efficient one (i.e., margin) in the rest of the experiments.

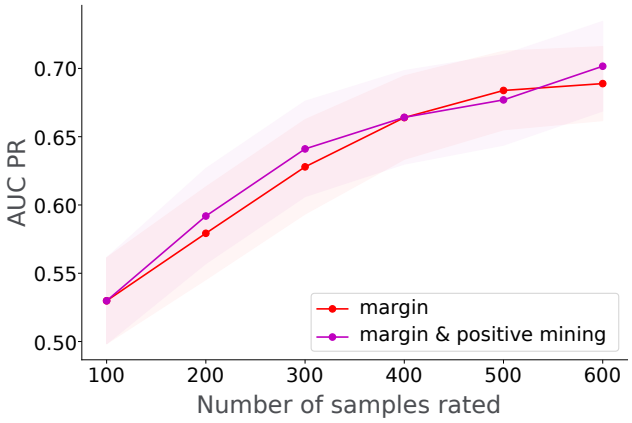


Figure 7: Model performance for two active learning methods: margin and the approach of [33] (margin & positive mining). Each • corresponds to an AL round. We show the AUC PR mean and standard error over all concepts.

Active learning batch size. Our prototype asks the user to annotate images across 5 rounds of active learning, 100 images per round. However, we can simultaneously change the number of images rated per round and the number of active learning rounds the user conducts. We evaluate the downstream effects of changing active learning batch size and number of rounds on model performance and time spent. We consider 3 batch sizes: small (50 images/batch), medium (100 images/batch), large (200 images/batch). We run repeated rounds of active learning with each of these settings, retraining the model after each round using CLIP representations. The results in Figure 8 show that, for a fixed amount of images rated, smaller batch sizes are better than larger, especially so in the beginning. This result is expected, because for a fixed rating budget, the smaller batch setting has the chance to update the model more frequently. While these results suggest that we should opt for a smaller batch size, there is still a trade-off between user time and performance, even when we have the same total number of samples rated. That is because model training takes about 1-2 minutes during which the user is idle, and so smaller batch sizes lead to longer time investment from the users. As a good compromise, we chose 100 as our batch size.

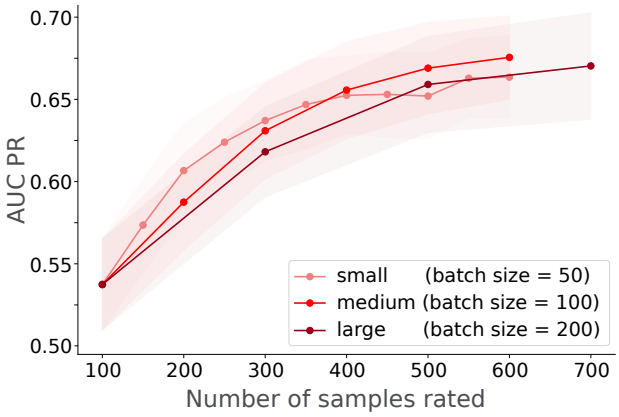


Figure 8: Model performance during active learning with 3 AL batch sizes: small (50), medium (100), large (200). Each • corresponds to an AL round. We show the AUC PR mean and standard error over all concepts.

Stronger pretrained model improves performance. Since our system leverages image-text co-embeddings to find relevant images and quickly train classifiers, a logical question is: how does changing the underlying embedding change the performance of the classifier? To do this, we compare CLIP versus ALIGN as the underlying embedding by replacing our pre-cached CLIP embeddings with ALIGN. We find that, with ALIGN, the AUROC of the final Agile model increased from 0.72 to 0.80 with a relative gain of 11.5%. The AUPR increased from 0.68 to 0.76, a relative gain of 13.1%. Furthermore, as Figure 6 demonstrates, both the ALIGN zero-shot and Agile models outperform their CLIP counterparts for almost every concept. This shows that building stronger image-text co-embeddings is foundational to improving the Agile Modeling process.

Appendix E. Additional active learning results

E.1 Additional metrics

We include here additional active learning results, measuring the amount of rating by user versus model performance. Figure 5 shows the results in terms of AUC ROC, F1 score, and accuracy. Note that, unlike AUC PR and AUC ROC, for computing the F1 score and accuracy one must choose a threshold on the model prediction score that determines whether a sample is on the positive or negative side of the decision boundary. For our trained MLP models, we used the common 0.5 threshold. For the zero-shot models, the threshold 0.5 is not a good choice, because the cosine similarities for both positive and negative are often smaller than this. In fact, [48] did an analysis of the right choice of threshold based on a human inspection on LAION-5B, and they recommend using the threshold 0.28 when using CLIP embeddings; we also use this threshold. We similarly chose 0.2 as a threshold when using ALIGN based on our own inspection.

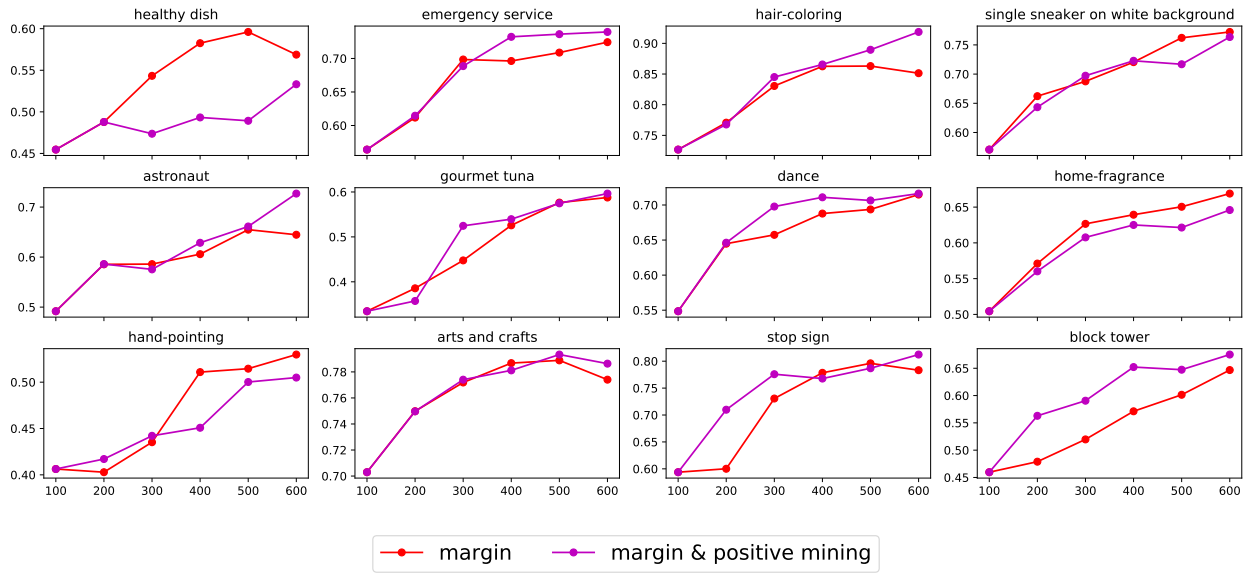


Figure 9: Results per concept for margin vs margin & positive mining of [33]. The each figure shows the AUC PR (on y-axis) for each active learning round (on x-axis) for the two methods.

Based on the results in Figure 5, we noticed the same consistent observations with all metrics: (1) the performance increases with every active learning round; (2) the performance increase is faster in the beginning, and starting to plateau in the later AL rounds; (3) the models that use ALIGN embeddings are consistently better than those using CLIP.

E.2 Margin versus Margin & Positive Mining

We show in detail the results per concept for the two active learning strategies considered in our paper: *margin sampling* and the *margin sampling & positive mining* of [33]. The results are shown in Figure 9. We observe that for the majority of the concepts the two methods are very close. Some exceptions include the concepts `healthy dish` and `hand pointing` for which *margin sampling* performs better, while for `block tower` *margin sampling & positive mining* works better. Overall it is not clear that one method is significantly better than the other.

Appendix F. Experiments with ImageNet21k

Our user study validates the Agile Modeling framework on a small number of concepts over a web-scale unlabeled dataset. Now, we confirm that our framework can be effectively applied across a larger number of concepts to achieve significant improvements over zero-shot baselines. Due to the scale of this experiment, we simulate the user annotations using a fully-labeled dataset.

Experimental setup. We use the ImageNet21k dataset [13] which contains 21k classes and over 14M images. Out of these we select a subset of both easy and difficult classes, as described below. Each class corresponds to a binary classification problem as before. We apply the Agile Modeling framework with the ImageNet21k training set as the unlabeled data pool, and the test set for evaluation. Ground-truth class labels included in the dataset simulate a user providing ratings. Since the Agile Modeling process starts at concept definition with no labeled data, we use the class name and its corresponding WordNet [32] description as positive text phrases in the text-to-image expansion step. As before, we use a batch size of 100 and 5 rounds of active learning. We use ALIGN embeddings.

Concept selection. We use a subset of 100 of the 21k concepts for evaluation. 50 "easy" concepts are selected at random from the ImageNet 1000 class list. Additionally, we aim to replicate the ambiguity and difficulty of our original concepts by carefully selecting 50 further concepts with the following criteria based the WordNet lexicographical hierarchy: (1) 2-20 hyponyms, to ensure visual variety, (2) more than 1 lemma, to ensure ambiguity, (3) not an animal or plant, which have objective descriptions. Of the 546 remaining concepts, our 50 "hard" concepts are selected at random. The full list of chosen concepts is the following:

50 easy concepts:

1. tree frog *(n00442981)*
2. harvestman *(n00453935)*
3. coucal *(n02911485)*
4. king penguin *(n02955540)*
5. Irish wolfhound *(n02957755)*
6. komondor *(n02973017)*
7. German shepherd *(n02975212)*
8. bull mastiff *(n02982599)*
9. Newfoundland *(n02992032)*
10. white wolf *(n03017168)*
11. ladybug *(n03181293)*
12. rhinoceros beetle *(n03340009)*
13. leafhopper *(n03365991)*
14. baboon *(n03413828)*
15. marmoset *(n03439814)*
16. Madagascar cat *(n03454211)*
17. analog clock *(n03484083)*
18. apiary *(n03525454)*
19. bathtub *(n03585875)*
20. bookcase *(n03592245)*
21. CD player *(n03727837)*
22. chain mail *(n03779000)*
23. chest *(n03996145)*
24. cornet *(n04041544)*
25. desk *(n04073948)*
26. desktop computer *(n04236702)*
27. gondola *(n04288272)*
28. letter opener *(n04422875)*
29. microwave *(n04571958)*
30. nail *(n04586581)*
31. patio *(n04970916)*
32. pickup *(n07681926)*
33. plane *(n07732747)*
34. pot *(n07805254)*
35. purse *(n07815588)*
36. racket *(n07819480)*
37. snowplow *(n07820497)*
38. sombrero *(n07820814)*
39. stopwatch *(n07850083)*
40. strainer *(n07860988)*
41. theater curtain *(n07867883)*
42. ice cream *(n07869391)*
43. pretzel *(n07907161)*
44. cauliflower *(n07918028)*
45. acorn squash *(n07933891)*
46. lemon *(n08663860)*
47. pizza *(n09213565)*
48. burrito *(n09305031)*
49. hen-of-the-woods *(n13908580)*
50. ear *(n14899328)*

50 hard concepts:

1. dive *(n00442981)*
2. fishing *(n00453935)*
3. buffer *(n02911485)*
4. caparison *(n02955540)*
5. capsule *(n02957755)*
6. cartridge holder *(n02973017)*
7. case *(n02975212)*
8. catch *(n02982599)*
9. cellblock *(n02992032)*
10. chime *(n03017168)*
11. detector *(n03181293)*
12. filter *(n03340009)*
13. floor *(n03365991)*
14. game *(n03413828)*
15. glider *(n03439814)*
16. grapnel *(n03454211)*
17. handcart *(n03484083)*
18. holder *(n03525454)*
19. ironing *(n03585875)*
20. jail *(n03592245)*
21. mat *(n03727837)*
22. module *(n03779000)*
23. power saw *(n03996145)*
24. radio *(n04041544)*
25. religious residence *(n04073948)*
26. sleeve *(n04236702)*
27. spring *(n04288272)*
28. thermostat *(n04422875)*
29. weld *(n04571958)*
30. winder *(n04586581)*
31. pink *(n04970916)*
32. cracker *(n07681926)*

33. cress *(n07732747)*
34. mash *(n07805254)*
35. pepper *(n07815588)*
36. mustard *(n07819480)*
37. sage *(n07820497)*
38. savory *(n07820814)*
39. curd *(n07850083)*
40. dough *(n07860988)*
41. fondue *(n07867883)*
42. hash *(n07869391)*
43. Irish *(n07907161)*
44. sour *(n07918028)*
45. herb tea *(n07933891)*
46. top *(n08663860)*
47. bank *(n09213565)*
48. hollow *(n09305031)*
49. roulette *(n13908580)*
50. culture medium *(n14899328)*

Results. In Figure 10 we show the results of applying the Agile Modeling framework to ImageNet21k. We see a similar trend to our user experiments, with significant improvements over zero-shot baselines as well as continued improvement with each active learning round. We further observe that the "easy" concepts attained higher scores after the Agile Modeling process than the "hard" concepts. The zero-shot baseline differed significantly between the "easy" and "hard" concepts with scores of 0.29 and 0.11, respectively. The equivalent of 30 minutes of human work yields a 20% boost in AUC PR over the zero-shot baseline.

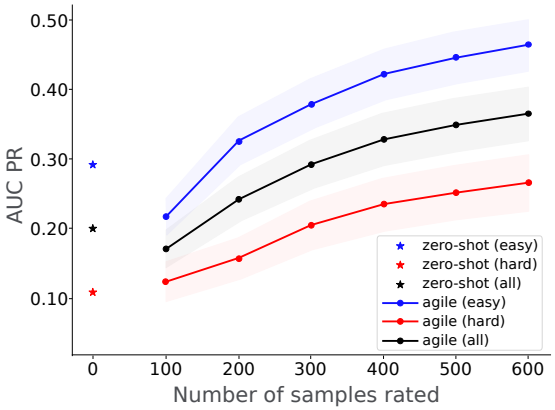


Figure 10: Model performance per amount of samples on ImageNet21k for easy and hard classes (AUC PR mean and std error over classes). Each • represents an AL round.

Appendix G. Concept difficulty

To be unbiased with respect to whom the rater is—whether it is the user or crowd raters—we decided to measure concept difficulty as the performance of a zero-shot model. We show the performance of the zero-shot model using CLIP embeddings for each concept, measured in terms of AUC PR on the test set, in Table 3.

With these scores, we can group the top 7 easiest and top 7 hardest concepts:

- top 7 easiest concepts: `emergency service`, `in-ear-headphones`, `single sneaker on white background`, `dance`, `pie-chart`, `hair-coloring`, `arts and crafts`
- top 7 hardest concepts: `gourmet tuna`, `healthy dish`, `hand-pointing`, `astronaut`, `block tower`, `home-fragrance`, `stop sign`

Concept	Score
gourmet tuna	0.37
healthy dish	0.46
hand-pointing	0.47
astronaut	0.48
block tower	0.49
home-fragrance	0.50
stop sign	0.51
emergency service	0.53
in-ear-headphones	0.55
single sneaker on white background	0.56
dance	0.61
pie-chart	0.66
hair-coloring	0.73
arts and crafts	0.74

Table 3: Difficulty score per concept, estimated as AUC PR of the zero-shot model using CLIP embeddings.

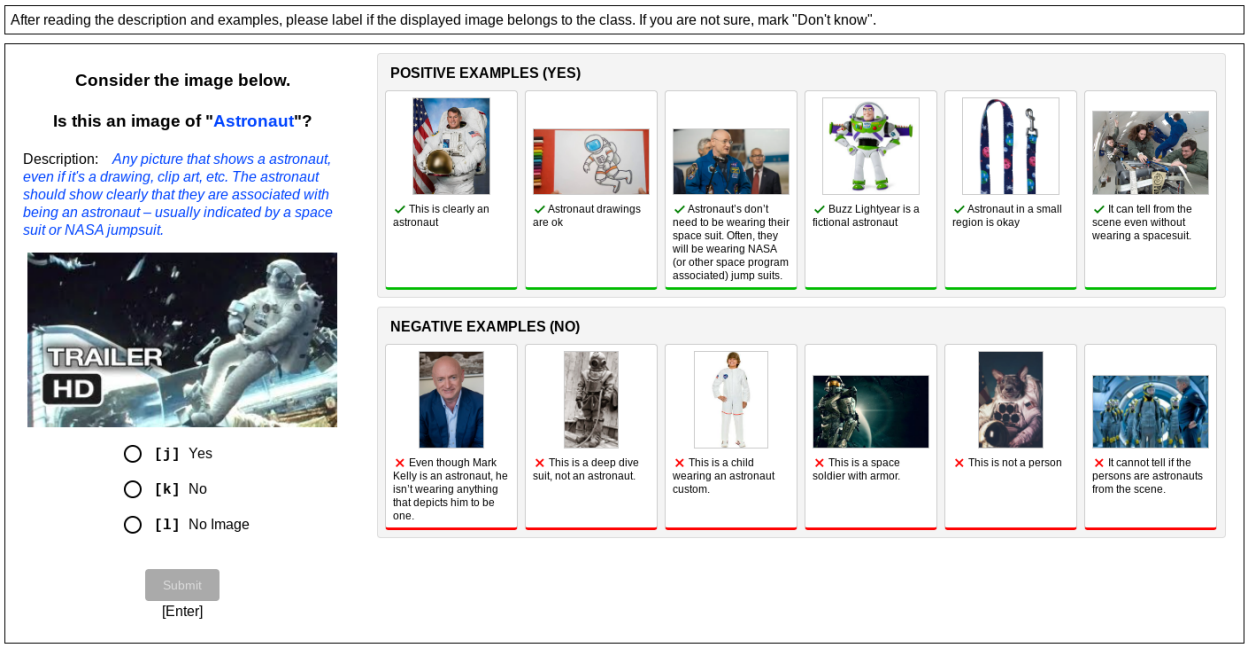


Figure 11: An example template we use for crowd labeling, for the `astronaut` concept.

Appendix H. Crowd task design

Crowd workers are onboarded to the binary image classification task then given batches of images to label, where each batch contains images from the same concept type to minimize cross-concept mislabeling. In Figure 11 we show the task we present to crowd workers for image classification. The template contains the image to classify, as well as a description of the image concept and a set of positive and negative examples created by the user who created the concept. Each image is sent to three crowd workers and the label is decided by majority vote.

Appendix I. Experimental details

All models are multilayer perceptrons (MLP) that take image representations from a frozen pre-trained model as input and contain one or more hidden layers. For the first active learning step, we use a smaller MLP with 1 hidden layer of 16 units to prevent overfitting, while all active learning rounds and final model have 3 hidden layers of size 128. All models are trained using binary cross-entropy loss, a dropout rate of 0.5 and weight decay regularization with weight 10^{-4}. We use the Adam optimizer [22] with learning rate 10^{-4} and train for 10 epochs. To prevent overtriggering by the trained classifier, we sample 500k random images from the unlabeled set and automatically label them negative. During training, we upsample our labeled positives to be half the training set, while labeled negatives and the random negatives are each a quarter of the training set. All hyperparameters have been chosen on 2 held-out concepts.

Appendix J. User-in-the-loop vs crowd raters

We include additional results comparing active learning with the user in the loop with active learning using crowd raters. Figure 12 shows detailed results, per concept, for the three experimental settings `User-100`, `Crowd-100` and `Crowd-500` described in Section 4.3.2. We can notice how for difficult concepts (according to the difficulty scores in Appendix G) such as `healthy dish`, the performance

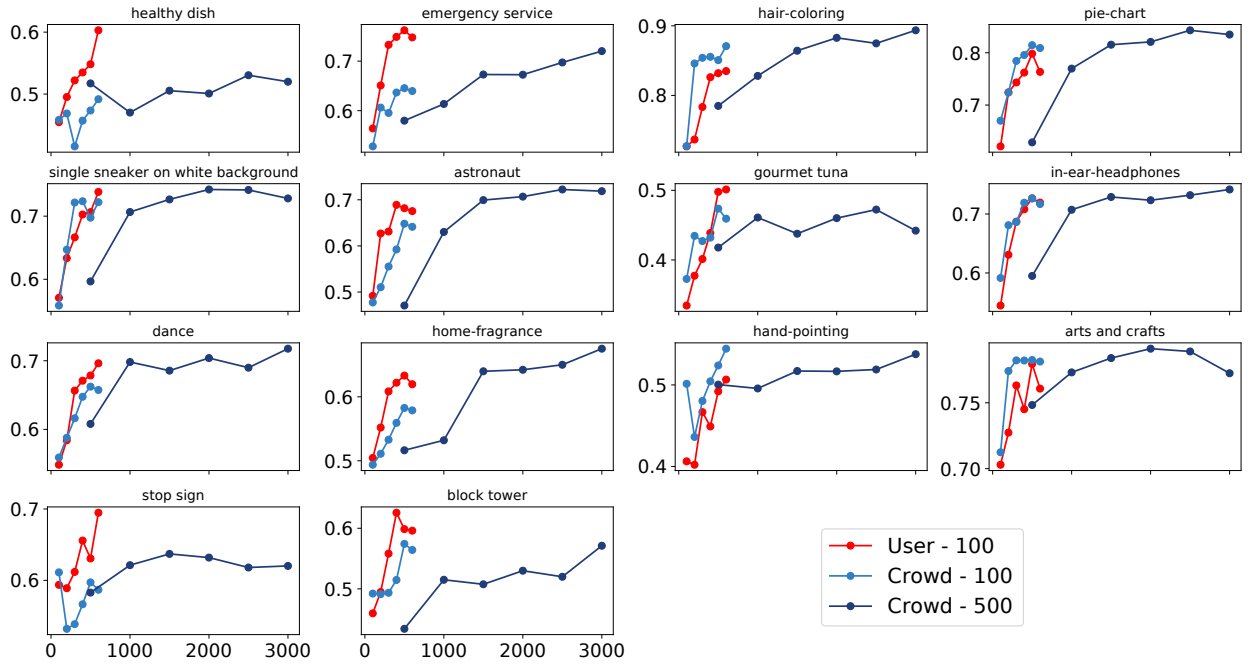
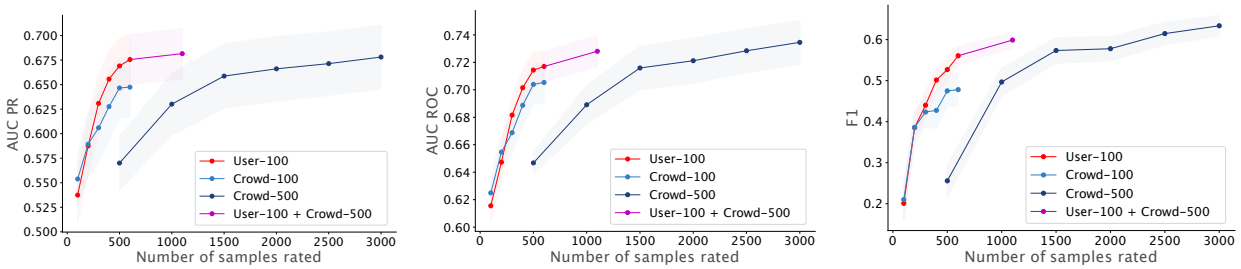


Figure 12: Results per concept comparing user model performance versus crowd. We show the AUC PR (y-axis) per number of samples rated (x-axis) for each of the three active learning experimental settings: user (batch size = 100), crowd (batch size = 100), and crowd (batch size = 500).



(a) AUC PR. (b) AUC ROC. (c) F1 score.

Figure 13: Model performance per amount of samples rated by the user and/or crowd raters. We also display an additional experimental setting `User-100 + Crowd-500`, where 5 rounds of user AL with batch size 100 are continued with another round of AL with crowd raters, with batch size 500. Mean and standard error over all concepts, for multiple metrics.

of the user models far exceeds that of the crowd raters, with far less samples. On the other hand, for easy concepts such as `hair coloring` the models trained with more data from crowd raters end up superseding the best user model.

Appendix K. Augmenting user labeling with crowdsourced ratings

One natural question to ask is what happens if we combine the benefits from doing active learning (AL) with users with those of AL with crowd raters. We considered such a setting. For each concept, we took the model trained after 5 rounds of AL with the user (setting `User-100` in Section 4.3.2) and we used it for another round of active learning with a larger batch size (500), this time rated by crowd workers. The results are shown in Figure 13, where we named this setting `User-100 + Crowd-500`. With additional data from the crowd raters, the model shows further improvements.