Transfer Learning by Borrowing Examples for Multiclass Object Detection

by

Joseph J. Lim

B.A., Computer Science, University of California - Berkeley, 2009

Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of

Master of Science
in Electrical Engineering and Computer Science
at the Massachusetts Institute of Technology

September 2012

Signature of Author: ______________________________
Department of Electrical Engineering and Computer Science
June 21, 2012

Certified by: ______________________________
Antonio Torralba
Associate Professor of Electrical Engineering and Computer Science
Thesis Supervisor

Accepted by: ______________________________
Leslie A. Kolodziejski
Professor of Electrical Engineering and Computer Science
Chair, Committee for Graduate Students

Transfer Learning by Borrowing Examples for Multiclass Object Detection

by Joseph J. Lim

Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of
Master of Science

Abstract

Despite the recent trend of increasingly large datasets for object detection, there still exist many classes with few training examples. To overcome this lack of training data for certain classes, we propose a novel way of augmenting the training data for each class by borrowing and transforming examples from other classes. Our model learns which training instances from other classes to borrow and how to transform the borrowed examples so that they become more similar to instances from the target class. Our experimental results demonstrate that our new object detector, with borrowed and transformed examples, improves upon the current state-of-the-art detector on the challenging SUN09 object detection dataset.

Thesis Supervisor: Antonio Torralba
Title: Associate Professor of Electrical Engineering and Computer Science

Acknowledgments

I would first like to thank my advisor, Professor Antonio Torralba. Not only has he been a great mentor for conducting scientific research, but also his endless passion and enthusiasm toward Computer Vision has been a great inspiration.

I would also like to thank to many of my previous advisors: Professor Jitendra Malik and Professor Max Welling, and my collaborators: Pablo Arbeláez, Myung Jin Choi, Chunhui Gu, Ruslan Salakhutdinov. They gave a big motivation on every problem I worked on. Also, MIT visionaries, Roger Grosse, Aditya Khosla, Tomasz Malisiewicz, Andrew Owens, Carl Vondrick, Jianxiong Xiao, Jenny Yuen, helped me going through many research obstacles by brain-storming and working together all day and night.

The National Science Foundation funded my research between 2009-2012 by the NSF Graduate Research Fellowship. I would like to thank to them for awarding the fellowship.

My parents, Bonguk and Kyungsun, and my brother, Yongwhan, always have been an ultimate source of encouragement and I would like to thank for their tremendous love, trust, and guide. Without them, I would never have been able to fall in love with research.

Thank to my wife, Eunice (Eunjee), for her unconditional love and support that enabled me do what I love to do always.

p.s. I would also like to thank to Vision01-Vision37, continent, and day machines for their dedicated work for 24 hours, 365 days.

Contents

List of Figures

Chapter 1

Introduction

CONSIDER building a *sofa* detector using a database of annotated images containing sofas and many other classes, as shown in Figure 1.1. One possibility would be to train the sofa detector using only the sofa instances. However, this would result in somewhat poor performance due to the limited size of the training set. An alternative is to build priors about the appearance of object categories and share information among object models of different classes. In most previous work, transfer of information between models takes place by imposing some regularization across model parameters. This is the standard approach both in the discriminative setting [1, 2, 14–17, 20, 21, 28] and in generative object models [3, 8, 9, 19, 24, 25].

In this thesis, we propose a different approach to transfer information across object categories. Instead of building object models in which we enforce regularization across the model parameters, we propose to directly share training examples from similar categories. In the example from Figure 1.1, we can try to use training examples from other classes that are similar enough in appearance, for instance *armchairs*. We could just add all the armchair examples to the sofa training set. However, not all instances of armchairs will look close enough to sofa examples to train an effective detector. Therefore, we propose a mechanism to select, among all training examples from other classes, which ones are closer to the *sofa* class. We can increase the number of instances that we can *borrow* by applying various transformations (e.g., stretching armchair instances horizontally to look closer to sofas). The transformations will also depend on the viewpoint. For instance, a frontal view of an armchair looks like a compressed sofa, whereas the side view of an armchair and a sofa often look indistinguishable. Our approach differs from generating new training examples by perturbing examples (e.g., adding mirrored or rotated versions) from its own class [13]. Rather, these techniques can be combined with our approach.

Our approach looks for the set of classes to borrow from, which samples to borrow, and what the best transformation for each example is. Our work has similarities with three pieces of work on transfer learning for object recognition. Miller et al. [19] propose a generative model for digits that shares transformations across classes. The generative model decomposes each model into an appearance model and a distribution over transformations that can be applied to the visual appearance to generate new samples. The set of transformations is shared across classes. In their work, the transfer

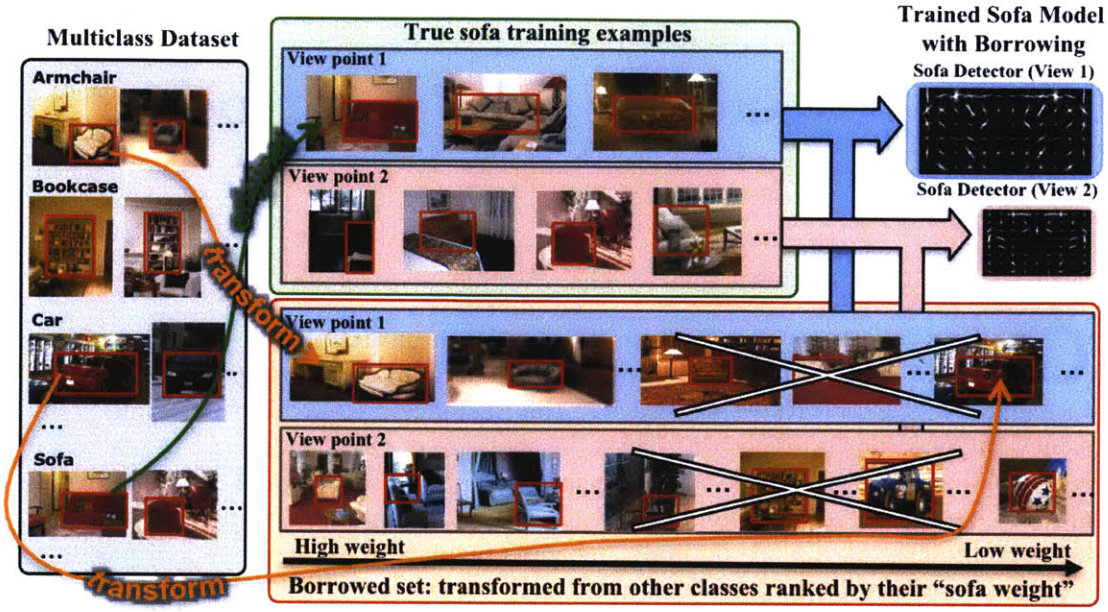


Figure 1.1. An illustration of training a sofa detector by borrowing examples from other related classes in the dataset. Our model can find (1) good examples to borrow, by *learning* a weight for each example, and (2) the best transformation for each training example in order to increase the borrowing flexibility. Transformed examples in blue (or red) box are more similar to the sofa's frontal (or side) view. Transformed examples, which are selected according to their learned weights, are trained for sofa together with the original sofa examples. (`X` on images indicates that they have low weights to be borrowed)

of information is achieved by sharing parameters across the generative models and not by reusing training examples. The work by Fergus et al. [11] achieves transfer across classes by learning a regression from features to labels. Training examples from classes similar to the target class are assigned labels between +1 and −1. This is similar to borrowing training examples but relaxing the confidence of the classification score for the borrowed examples. Wang et al. [29] assign rankings to similar examples, by enforcing the highest and lowest rankings for the original positive and negative examples, respectively, and requiring borrowed examples be somewhere in between. Both of these works rely on a pre-defined similarity metric (e.g. WordNet or aspect based similarity) for deciding which classes to share with.

Our method, on the other hand, learns which classes to borrow from as well as which examples to borrow within those classes as part of the model learning process.

Borrowing training examples becomes effective when many categories are available. When there are few and distinct object classes, as in the PASCAL dataset [6], the improvement may be limited. However, a number of other efforts are under way for building large annotated image databases with many categories [5, 22, 30]. As the number of classes grows, the number of sets of classes with similar visual appearances (e.g., the set of *truck, car, van, suv*, or *chair, armchair, swivel chair, sofa*) will increase, and the effectiveness of our approach will grow as well. In our experiments, we show that borrowing training examples from other classes results in improved performance upon the current state of the art detectors trained on a single class. In addition, we also show that our technique can be used in a different but related task. In some cases, we are interested in merging multiple datasets in order to improve the performance on a particular test set. We show that learning examples to merge results in better performance than simply combining the two datasets. Parts of this work in this thesis appeared previously at 2011 Neural Information Processing Systems (NIPS) [18].

Chapter 2

Learning to Borrow Examples

Consider the challenging problem of detecting and localizing objects from a wide variety of categories such as cars, chairs, and trees. Many current state-of-the-art object detection (and object recognition) systems use rather elaborate models, based on separate appearance and shape components, that can cope with changes in viewpoint, illumination, shape and other visual properties. However, many of these systems [4, 10] detect objects by testing sub-windows and scoring corresponding image patches $\mathbf{x}$ with a *linear function* of the form: $y = \boldsymbol{\beta}^\top \Phi(\mathbf{x})$, where $\Phi(\mathbf{x})$ represents a vector of different image features, and $\boldsymbol{\beta}$ represents a vector of model parameters. Here on, we denote $\Phi(\mathbf{x})$ as $\mathbf{x}$ for the simplicity.

In this work, we focus on training detection systems for multiple object classes. Our goal is to develop a novel framework that enables borrowing examples from related classes for a generic object detector, making minimal assumptions about the type of classifier, or image features used.

2.1 Loss Function for Borrowing Examples

Consider a classification problem where we observe a dataset $\mathcal{D} = \{\mathbf{x}_i, y_i\}_{i=1}^n$ of n labeled training examples. Each example belongs to one of C classes (e.g. 100 object classes), and each class $c \in \mathcal{C} = \{1, ..., C\}$ contains a set of n_c labeled examples. We let $\mathbf{x}_i \in \mathrm{R}^D$ denote the input feature vector of length D for the training case i, and y_i be its corresponding class label. Suppose that we are also given a separate background class, containing b examples. We further assume a binary representation for class labels[1], i.e. $y_i \in \mathcal{C} \cup \{-1\}$, indicating whether a training example i belongs to one of the given C classes, or the "negative" background class[2].

For a standard binary classification problem, a commonly used approach is to min-

[1] This is a standard "1 *vs.* all" classification setting.

[2] When learning a model for class c, all other classes can be considered as "negative" examples. In this work, for clarity of presentation, we will simply assume that we are given a separate background class.

imize:

$$\min_{\boldsymbol{\beta}^c}\left(\sum_{i=1}^{n_c+b}\texttt{Loss}\big(\boldsymbol{\beta}^c\cdot\mathbf{x}_i,\mathrm{sign}(y_i)\big)+\lambda R(\boldsymbol{\beta}^c)\right),\tag{2.1}$$

where i ranges over the positive and negative examples of the target class c; $\boldsymbol{\beta}^c \in \mathrm{R}^D$ is the vector of unknown parameters, or regression coefficients, for class c; $\texttt{Loss}(\cdot)$ is the associated loss function; and $R(\cdot)$ is a regularization function for $\boldsymbol{\beta}$.

Now, consider learning which other training examples from the entire dataset $\mathcal{D}$ our target class c could borrow. The key idea is to learn a vector of weights $\mathbf{w}^c$ of length $n+b$, such that each w_i^c would represent a soft indicator of how much class c borrows from the training example x_i. Soft indicator variables w_i^c will range between 0 and 1, with 0 indicating borrowing none and 1 indicating borrowing the entire example as an additional training instance of class c. All true positive examples belonging to class c, with $y_i = c$, and all true negative examples belonging to the background class, with $y_i = -1$, will have $w_i^c = 1$, as they will be used fully. Remaining training examples will have w_i^c between 0 and 1. Our proposed regularization model takes the following form:

$$\sum_{c\in C}\min_{\boldsymbol{\beta}^c}\min_{\mathbf{w}^{*,c}}\left(\sum_{i=1}^{n+b}(1-w_i^{*,c})\texttt{Loss}\big(\boldsymbol{\beta}^c\cdot x_i,\mathrm{sign}(y_i)\big)+\lambda R(\boldsymbol{\beta}^c)+\Omega_{\lambda_1,\lambda_2}(\mathbf{w}^{*,c})\right),\tag{2.2}$$

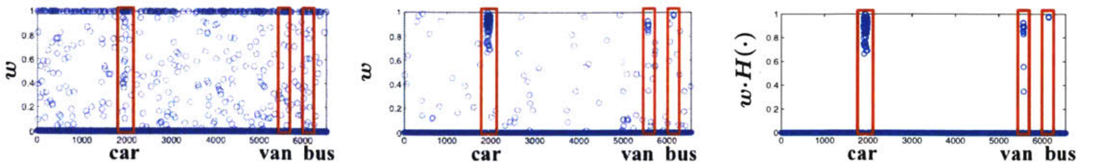
subject to $w_i^c = 1$ for $y_i = -1$ *or* c, and $0 \leq w_i^c \leq 1$ for all other i, where we defined[3] $\mathbf{w}^* = 1 - \mathbf{w}$, and where i ranges over *all training examples* in the dataset. We further define $\Omega(\mathbf{w}^*)$ as:

$$\Omega_{\lambda_1,\lambda_2}(\mathbf{w}^*) = \lambda_1\sum_{l\in C}\sqrt{n_l}\|\mathbf{w}^*_{(l)}\|_2 + \lambda_2\|\mathbf{w}^*\|_1,\tag{2.3}$$

where $\mathbf{w}^*_{(l)}$ represents a vector of weights for class l, with $\mathbf{w}^*_{(l)} = (w^*_{j_1}, w^*_{j_2}, \cdots, w^*_{j_{n_l}})$ for $y_{j_m} = l$. Here, $\Omega(\cdot)$ regularizes $\mathbf{w}^{*,c}$ using a sparse group lasso criterion [31]. Its first term can be viewed as an intermediate between the L_1 and L_2-type penalty. A pleasing property of L_1-L_2 regularization is that it performs variable selection at the group level. The second term of $\Omega(\cdot)$ is an L_1-norm, which keeps the sparsity of weights at the individual level.

The overall objective of Eq (2.2) and its corresponding regularizer $\Omega(\cdot)$ have an intuitive interpretation. The regularization term encourages borrowing *all examples* as new training instances for the target class c. Indeed, setting corresponding regularization parameters λ_1 and λ_2 to high enough values (i.e. forcing $\mathbf{w}$ to be an all $\mathbf{1}$ vector) would amount to borrowing all examples, which would result in learning a "generic" object detector. On the other hand, setting $\lambda_1 = \lambda_2 = 0$ would recover the original standard objective of Eq (2.1), without borrowing any examples. Figure 2.1b displays learned w_i

[3] For clarity of presentation, throughout the rest of the thesis, we will use the following identity $\mathbf{w}^* = 1 - \mathbf{w}$.



(a) Only with L_1-norm

(b) Learned by $\Omega(\cdot)$ without the Heaviside step function

(c) Learned by $\Omega(\cdot)$ with the Heaviside step function

Figure 2.1. **Learning to borrow for the target truck class:** Learned weights $\mathbf{w}^{\text{truck}}$ for 6547 instances using (a) L_1-norm; (b) $\Omega(\cdot)$ regularization; and (c) $\Omega(\cdot)$ with symmetric borrowing constraint.

for 6547 instances to be borrowed by the *truck* class. Observe that classes that have similar visual appearances to the target *truck* class (e.g. *van*, *bus*) have w_i close to 1 and are grouped together (compare with Figure 2.1a, which only uses an L_1 norm).

We would also like to point out an analogy between our model and various other transfer learning models that regularize the $\boldsymbol{\beta}$ parameter space [7, 26]. The general form applied to our problem setting takes the following form:

$$\sum_{c \in \mathcal{C}} \min_{\boldsymbol{\beta}^c} \left(\sum_i \texttt{Loss}(\boldsymbol{\beta}^c \cdot \mathbf{x}_i, \operatorname{sign}(y_i)) + \lambda R(\beta^c) + \gamma \|\boldsymbol{\beta}^c - \frac{1}{C} \sum_{k=1}^{C} \boldsymbol{\beta}^k \|_2^2 \right). \tag{2.4}$$

The model in Eq (2.4) regularizes all $\boldsymbol{\beta}^c$ to be close to a single mode, $\frac{1}{C}\sum_k \boldsymbol{\beta}^k$. This can be further generalized so that $\boldsymbol{\beta}^c$ is regularized toward one of many modes, or "super-categories", as pursued in [23]. Contrary to previous work, our model from Eq (2.2) regularizes weights on all training examples, rather than parameters, across all categories. This allows us to *directly learn* both: which examples and what categories we should borrow from. We also note that model performance could potentially be improved by introducing additional regularization across model parameters.

■ 2.2 Learning

Solving our final optimization problem, Eq (2.2), for $\mathbf{w}$ and $\boldsymbol{\beta}$ jointly is a non-convex problem. We therefore resort to an iterative algorithm based on the fact that solving for $\boldsymbol{\beta}$ given $\mathbf{w}$ and for $\mathbf{w}$ given $\boldsymbol{\beta}$ are convex problems. The algorithm will iterate between (1) solving for $\boldsymbol{\beta}$ given $\mathbf{w}$ based on [10], and (2) solving for $\mathbf{w}$ given $\boldsymbol{\beta}$ using the block coordinate descent algorithm [12] until convergence. We initialize the model by setting w_i^c to 1 for $y_i = c$ and $y_i = -1$, and to 0 for all other training examples. Given this initialization, the first iteration is equivalent to solving C separate binary classification problems of Eq (2.1), when there is no borrowing[4]

Even though most irrelevant examples have low borrowing indicator weights w_i, it is ideal to clean up these noisy examples. To this end, we introduce a symmetric

[4] In this thesis, we iterate only once, as it was sufficient to borrow similar examples (see Figure 2.1).

borrowing constraint: if a *car* class does not borrow examples from *chair* class, then we would also like for the *chair* class not to borrow examples from the corresponding *car* class. To accomplish this, we multiply w_i^c by $H(\bar{w}_c^{y_i} - \epsilon)$, where $H(\cdot)$ is the Heaviside step function. We note that w_i^c refers to the weight of example x_i to be borrowed by the target class c, whereas $\bar{w}_c^{y_i}$ refers to the average weight of examples that class y_i borrows from the target class c. In other words, if the examples that class y_i borrows from class c have low weights on average (i.e. $\bar{w}_c^{y_i} < \epsilon$), then class c will not borrow example x_i, as this indicates that classes c and y_i may not be similar enough. The resulting weights after introducing this symmetric relationship are shown in Figure 2.1c.

Chapter 3

Borrowing Transformed Examples

So far, we have assumed that each training example is borrowed as is. Here, we describe how we apply transformations to the candidate examples during the training phase. This will allow us to borrow from a much richer set of categories such as *sofa-armchair*, *cushion-pillow*, and *car-van*. There are three different transformations we employ: translation, scaling, and affine transformation.

■ 3.1 Translation and scaling

Translation and scaling are naturally inherited into existing detection systems during scoring. Scaling is resolved by scanning windows at multiple scales of the image, which typical sliding-window detectors already do. Translation is implemented by relaxing the location of the ground-truth bounding box B_i. Similar to Felzenszwalb et al. [10]'s approach of finding latent positive examples, we extract $\mathbf{x}_i$ from multiple boxes that have a significant overlap with B_i, and select a candidate example that has the smallest $\texttt{Loss}(\boldsymbol{\beta}^c \cdot \mathbf{x}_i, \text{sign}(y_i))$.

■ 3.2 Affine transformation

We also change aspect ratios of borrowed examples so that they look more alike (as in *sofa-armchair* and *desk lamp-floor lamp*). Our method is to transform training examples to every canonical aspect ratio of the target class c, and find the best candidate for borrowing. The canonical aspect ratios can be determined by clustering aspect ratios of all ground-truth bounding boxes [10], or based on the viewpoints, provided we have labels for each viewpoint. Specifically, suppose that there is a candidate example $\mathbf{x}_i$ to be borrowed by the target class c and there are L canonical aspect ratios of c. We transform $\mathbf{x}_i$ into $\mathbf{x}_i^l$ by resizing one dimension so that $\{\mathbf{x}_i^l\}_{0 \le l \le L}$ contains all L canonical aspect ratios of c (and $\mathbf{x}_i^0 = \mathbf{x}_i$). In order to ensure that only one candidate is generated from $\mathbf{x}_i$, we select a single transformed example $\mathbf{x}_i^l$, for each i, that minimizes $\texttt{Loss}(\boldsymbol{\beta}^c \cdot \mathbf{x}_i^l, \text{sign}(y_i))$. Note that this final candidate can be selected during every training iteration, so that the best selection can change as the model is updated.

Figure 1.1 illustrates the kind of learning our model performs. To borrow examples for *sofa*, each example, $\mathbf{x}_i$, in the dataset is transformed into the frontal and side view

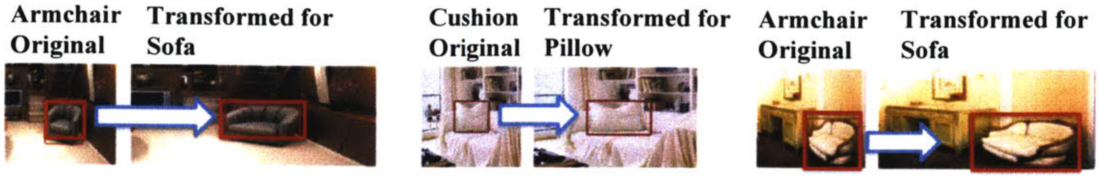


Figure 3.1. Illustration of Transformation: Each example is transformed into different candidate aspect ratios so that they can look most alike with the target class. The transformation with the smallest `Loss`(·) is selected for borrowing.

aspect ratios of *sofa*. The transformed example that has the smallest `Loss`(·) is selected for borrowing. Each example is then assigned a borrowing weight using Eq (2.2). Finally, the new *sofa* detector is trained using borrowed examples together with the original *sofa* examples. We refer the detector trained without affine transformation as the **borrowed-set** detector, and the one trained with affine transformation as the **borrowed-transformed** detector.

Figure 3.1 illustrates the kind of transformations we perform. An *armchair* example in the first box is transformed to the frontal view aspect ratio of *sofa*, because their transformation to the frontal view had the lowest `Loss`(·) by the sofa model. On the other hand, an *armchair* example in the third box is transformed to the side view aspect ratio of *sofa*, because their transformation to the side view scored the lowest by the sofa model. After scoring and selecting transformations for all *armchair* examples, they will be used in Eq (2.2) for training a *sofa* detector.

Chapter 4

Experimental Results

We present experimental results on two standard datasets: the SUN09 dataset [30] and the PASCAL VOC 2007 challenge [6]. The SUN09 dataset contains 4,082 training images and 9,518 testing images. We selected the top 100 object categories according to the number of training examples. These 100 object categories include a wide variety of classes such as *bed*, *car*, *stool*, *column*, and *flowers*, and their distribution is heavy tailed varying from 1356 to 8 instances. The PASCAL dataset contains 2,051 training images and 5,011 testing images, belonging to 20 different categories. For both datasets, we use the PASCAL VOC 2008 evaluation protocol [6].

The large variations of number of instances between object categories means that each class has a very different ratio of the number positive images to the number of negative images. Whichever class has relatively more negative images than positive images is effectively becoming a harder dataset. Therefore, it is impossible to directly compare one class detector to the other class detector. During the testing phase, in order to enable a direct comparison between various detectors, we measure the detection score of class c as the mean Average Precision (AP) score across all positive images that belong to class c and randomly sub-sampled negative images, so that the ratio between positive and negative examples remains the same across all classes.

Our experiments are based on one of the state-of-art detectors [10]. Following [10], we use a hinge loss for $\mathtt{Loss}(\cdot)$ and a squared L_2-norm for $R(\cdot)$ in Eq (2.2), where every detector contains two root components. There are four controllable parameters: λ, λ_1, λ_2, and ϵ (see Eq (2.2)). We used the same λ as in [10]. λ_1 and λ_2 were picked based on the validation set, and ϵ was set to 0.6. In order to improve computation time, we threshold each weight w_i so that it will either be 0 or 1.

Figure 4.1 shows performances when we vary the number of training examples for each original class. Log-linear relationship between the number of examples and the AP performance is shown clearly on the graph.

We perform two kinds of experiments: (1) borrowing examples from other classes within the same dataset, and (2) borrowing examples from the same class that come from a *different* dataset. Both experiments require identifying which examples are beneficial to borrow for the target class.

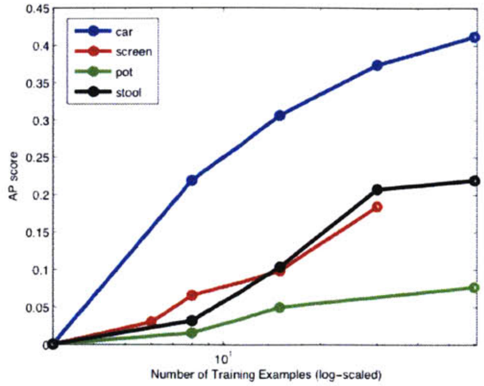


Figure 4.1. Performances on varied number of original training examples: We varied the number of original-only training examples and tested on the same test set. The performances have a log-linear increasing trend against the number of training examples.

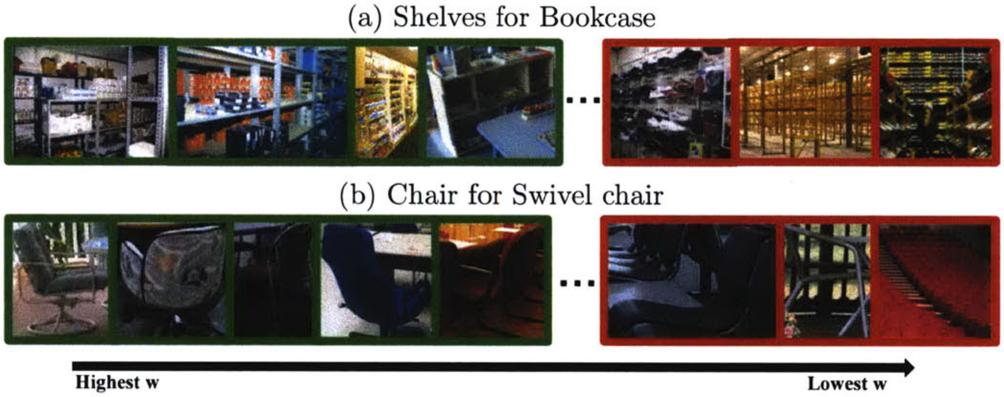
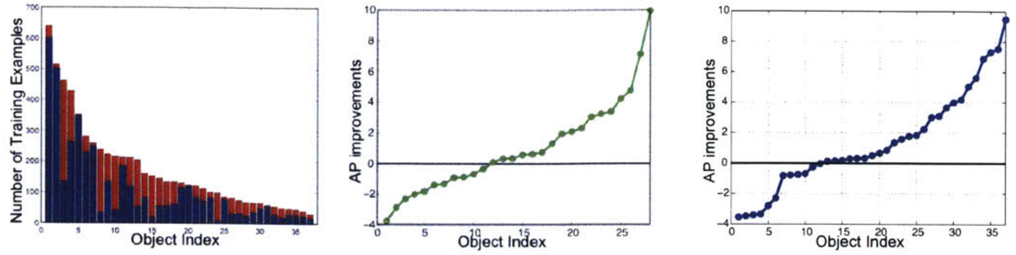


Figure 4.2. Borrowing Weights: Examples are ranked by learned weights, w: (a) *shelves* examples to be borrowed by the *bookcase* class and (b) *chair* examples to be borrowed by the *swivel chair* class. Both show that examples with higher w are more similar to the target class. (green: borrowed, red: not borrowed)

4.1 Borrowing from Other Classes

We first tested the ability of our model to identify a useful set of examples to borrow from *other classes* in order to improve the detection quality on the SUN09 dataset. A unique feature of the SUN09 dataset is that all images were downloaded from the internet without making any effort to create a uniform distribution over object classes. We argue that this represents a much more realistic setting, in which some classes contain a lot of training data and many other classes contain little data.

Among 100 classes, our model learned that there are 28 and 37 classes that can borrow from other classes without and with transformations, respectively. Table 4.1 shows some of the learned borrowing relationships along with their improvements. Most



(a) Number of examples before/after borrowing

(b) Borrowed-set AP improvements

(c) Borrowed-transformed AP improvements

Figure 4.3. (a) Number of examples used for training per class before borrowing (blue) and after borrowing (red). Categories with fewer examples tend to borrow more examples. AP improvements (b) without and (c) with transformations, compared to the single detector trained only with the original examples. Note that our model learned to borrow from (b) 28 classes, and (c) 37 classes.

Original Class	Without transformation		With transformation	
	Borrowed Classes	AP improvement	Borrowed Classes	AP improvement
Truck	car, van	+7.14	car, van	+9.49
Shelves	bookcase	+0.17	bookcase	+4.73
Car	truck, van	+1.07	truck, van, **bus**	+1.78
Desk lamp	∅	N/A	**floor lamp**	+0.30
Toilet	∅	N/A	**sink, cup**	-0.68

Table 4.1. Learned borrowing relationships: Most discovered relations are consistent with human subjective judgment. Classes that were borrowed only with transformations are shown in bold.

are consistent with human subjective judgment. Interestingly, our model excluded *bag*, *slot machine*, *flag*, and *fish*, among others, from borrowing. Many of those objects have quite distinctive visual appearances compared to other object categories.

We next analyzed the quality of borrowed examples along with their learned weights. Figure 4.2 shows borrowed examples along with their relative orders according to the borrowing indicator weights, w_i. Note that our model learns quite reliable weights: for example, *chair* examples in green box are similar to the target *swivel chair* class, whereas examples in red box are either occluded or very atypical.

Figure 4.3 further displays AP improvements of the borrowed-set and borrowed-transformed detectors, against standard single detectors. Observe that over 20 categories benefit in various degrees from borrowing related examples. Among borrowed-transformed detectors, the categories with the largest improvements are *truck* (9.49), *picture* (7.54), *bus* (7.32), *swivel chair* (6.88), and *bookcase* (5.62). We note that all of these objects borrow visual appearance from other related frequent objects, including *car*, *chair*, and *shelves*. Five objects with the largest decrease in AP include *plate* (-3.53), *fluorescent tube* (-3.45), *ball* (-3.21), *bed* (-2.69), and *microwave* (-2.52). Model performance often deteriorates when our model discovers relationships that are not ideal (e.g. *toilet* borrowing *cup* and *sink*; *plate* borrowing *mug*).

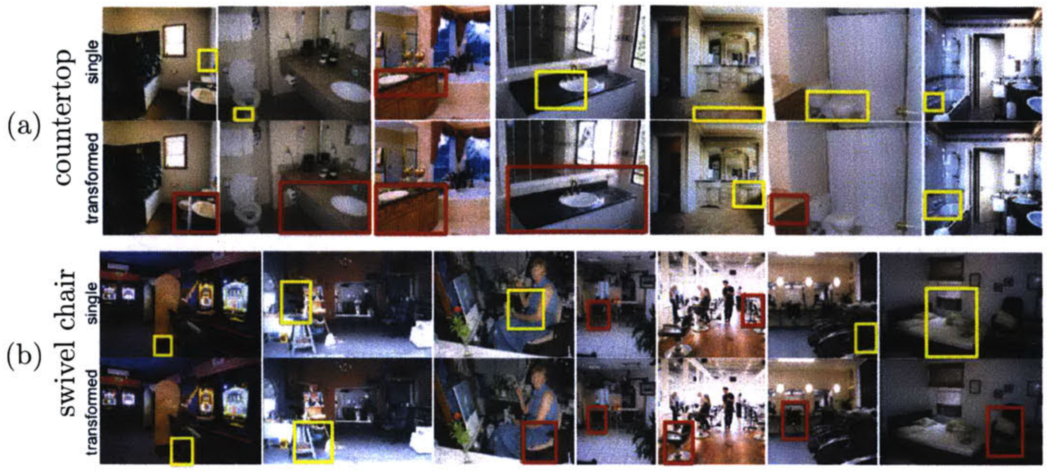


Figure 4.4. **Detection results** on random images containing the target class. Only the most confident detection is shown per image. For clearer visualization, we do not show images where both detectors have large overlap. Our detectors (2nd/4th row) show better localizations than single detectors (1st/3rd row). (red: correct detection, yellow: false detection)

Number of Training Examples	1-30	31-50	51-100	101-150	> 150	ALL
Borrowed-set	1.69	0.48	0.43	0.48	0.13	0.75
Borrowed-Transformed	2.75	2.57	0.94	0.81	0.17	1.49

Table 4.2. **Borrowing rates** for the borrowed-set and borrowed-transformed models. Borrowing rate is defined as the ratio of the number of borrowed examples to the number of original examples.

Table 4.2 further breaks down borrowing rates as a function of the number of training examples, where a borrowing rate is defined as the ratio of the total number of borrowed examples to the number of original training examples. Observe that borrowing rates are much higher when there are fewer training examples (see also Figure 4.3a). On average, the borrowed-set detectors borrow 75% of the total number of original training examples, whereas the borrowed-transformed detectors borrow about twice as many examples, 149%.

Table 4.3 shows AP improvements of our methods. Borrowed-set improve 1.00 and borrowed-transformed detectors improve 1.36. This is to be expected as introducing transformations allows us to borrow from a much richer set of object classes. We also compare to a baseline approach, which uses all examples in the borrowed classes of borrowed-transformed method. For example, if class A borrows some examples from class B and C using borrowed-transformed method, then the baseline approach uses all examples from class A, B, and C without any selection. Note that this baseline approach improves only 0.30 compared to 1.36 of our method.

Finally, Figure 4.4 displays detection results. Single and borrowed-transformed detections are visualized on test images, chosen at random, that contain the target class. In many cases, transformed detectors are better at localizing the target object,

Methods	Borrowed-set	All examples from the same classes	Borrowed-Transformed
AP w/o borrowing	14.99	16.59	16.59
AP improvements	+1.00	+0.30	+1.36

Table 4.3. AP improvements of the borrowed-set and borrowed-transformed detectors. We also compared borrowed-transformed method against the baseline approach borrowing all examples, without any selection of examples, from the same classes our method borrows from. 2nd row shows the average AP score of the detectors without any borrowing in the classes used for borrowed-set or borrowed-transformed.

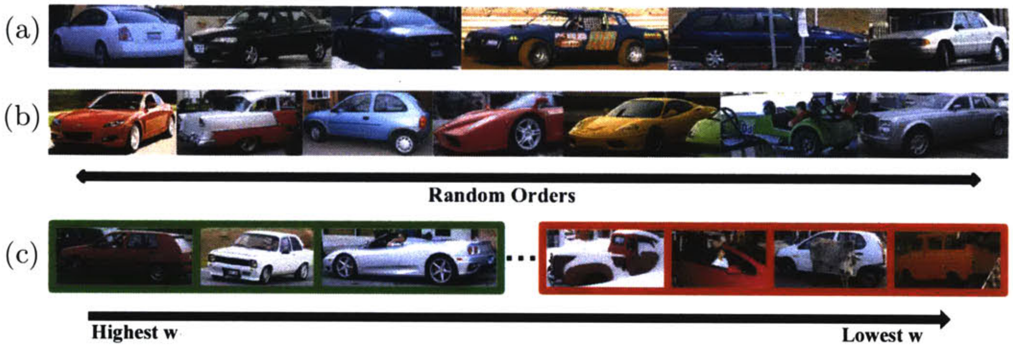
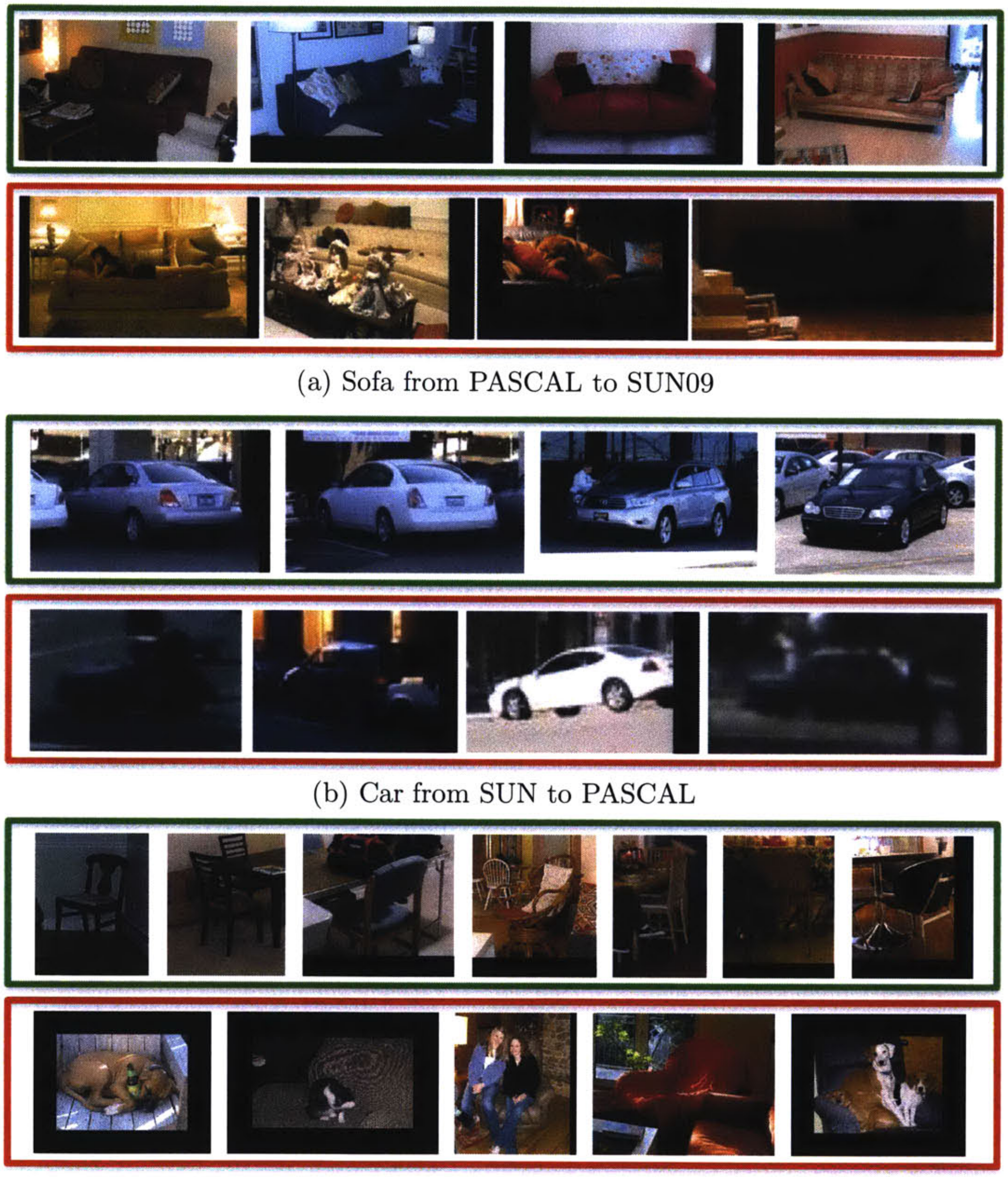


Figure 4.5. SUN09 borrowing PASCAL examples: (a) Typical SUN09 car images, (b) Typical PASCAL car images, (c) PASCAL car images sorted by learned borrowing weights. (c) shows that examples are sorted from canonical view points (left) to atypical or occluded examples (right). (green: borrowed, red: not borrowed)

even when they fail to place a bounding box around the full object. We also note that borrowing similar examples tends to introduce some confusions between related object categories. However, we argue that this type of failure is much more tolerable compared to the single detector, which often has false detections of completely unrelated objects.

■ 4.2 Borrowing from Other Datasets

Combining datasets is a non-trivial task as different datasets contain different biases. Consider training a car detector that is going to be evaluated on the PASCAL dataset. The best training set for such a detector would be the dataset provided by the PASCAL challenge, as both the training and test sets come from the same underlying distribution. In order to improve model performance, a simple mechanism would be to add additional training examples. For this, we could look for other datasets that contain annotated images of cars – for example, the SUN09 dataset. However, as the PASCAL and SUN09 datasets come with different biases, many of the training examples from SUN09 are not as effective for training when the detector is evaluated on the PASCAL dataset – a problem that was extensively studied by [27]. Here, we show that, instead of simply mixing the two datasets, our model can select a useful set of examples from the SUN09



(a) Sofa from PASCAL to SUN09

(b) Car from SUN to PASCAL

(c) Chair from PASCAL to SUN

Figure 4.6. Highest and Lowest borrowing weight examples: We show three different borrowing relationships (sofa, car, and chair). Green box shows top examples borrowed, and red box shows worst examples (hence not borrowed).

	SUN09	PASCAL	SUN09	SUN09
	only	only	+PASCAL	+borrow PASCAL
car	43.31	39.47	43.64	**45.88**
person	45.46	28.78	46.46	**46.90**
sofa	12.96	11.97	12.86	**15.25**
chair	18.82	13.84	18.18	**20.45**
mean	30.14	23.51	30.29	**32.12**
Diff.		-6.63	+0.15	**+1.98**

(a) Testing on the SUN09 dataset

	PASCAL	SUN09	PASCAL	PASCAL
	only	only	+SUN09	+borrow SUN09
car	49.58	40.81	49.91	**51.00**
person	23.58	22.31	26.05	**27.05**
sofa	19.91	13.99	20.01	**22.17**
chair	14.23	14.20	**19.06**	18.55
mean	26.83	22.83	28.76	**29.69**
Diff.		-4.00	+1.93	**+2.86**

(b) Testing on the PASCAL 2007 dataset

Table 4.4. Borrowing from other datasets: AP scores of various detectors: "SUN09 only" and "PASCAL only" are trained using the SUN09 dataset [30] and the PASCAL dataset [6] without borrowing any examples. "SUN09+PASCAL" is trained using positive examples from both SUN09 and PASCAL. and negative examples from the target dataset. "PASCAL+borrow SUN09" and "SUN09+borrow PASCAL" borrow selected examples from another dataset for each target dataset using our method. Note that "SUN09 only" and "PASCAL only" are classifiers trained by the *state-of-the-art* algorithm. The last Diff row shows AP improvements over the "standard" *state-of-art* detector trained on the target dataset (*column 1*).

for the PASCAL dataset, and vice-versa.

Figure 4.5 and Figure 4.6 show the kind of borrowing our model performs. Figure 4.5a,b display typical car images from the SUN09 and PASCAL datasets. Compared to SUN09, PASCAL images display a much wider variety of car types, with different viewpoints and occlusions. Figure 4.5c further shows the ranking of PASCAL examples by $w_i^{\text{SUN09 car}}$ for $i \in \mathcal{D}_{\text{PASCAL}}$. Observe that images with high w match the canonical representations of SUN09 images much better compared to images with low w. Figure 4.6 lists the best and worst object exemplars according to its borrowing weight against the target dataset.

Table 4.4 shows performances of four different detectors. Observe that detectors trained on the target dataset (*column 1*) outperform ones trained using another dataset (*column 2*). This shows that there exists a significant difference between the two datasets, which agrees with previous work [27]. Next, we tested detectors by simply combining positive examples from both datasets and using negative examples from the target dataset (*column 3*). On the SUN09 test set, the improvement was not significant, and on the PASCAL test set, we observed slight improvements. Detectors trained by our model (*column 4*) substantially outperformed single detectors as well as ones that were trained mixing the two datasets. The detectors (*columns 1* and *2*) were trained using the *state-of-art* algorithm [10].

Chapter 5

Conclusion

In this thesis we presented an effective method for transfer learning across object categories. The proposed approach consists of searching similar object categories using sparse grouped Lasso framework, and borrowing examples that have similar visual appearances to the target class. We further demonstrated that our method, both with and without transformation, is able to find useful object instances to borrow, resulting in improved accuracy for multi-class object detection compared to the state-of-the-art detector trained only with examples available for each class. Also, we presented another result on borrowing examples between datasets. Both of these results suggest a good evidence on a visual similarity between classes and datasets, and also usefulness of sharing for removing biases across datasets and labels.

Bibliography

[1] Y. Aytar and A. Zisserman. Tabula rasa: Model transfer for object category detection. In *International Conference on Computer Vision*, 2011.

[2] E. Bart and S. Ullman. Cross-generalization: learning novel classes from a single example by feature replacement. In *Computer Vision and Pattern Recognition*, 2005.

[3] E. Bart, I. Porteous, P. Perona, and M. Welling. Unsupervised learning of visual taxonomies. In *Computer Vision and Pattern Recognition*, 2008. doi: 10.1109/CVPR.2008.4587620.

[4] N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition*, 2005.

[5] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition*, 2009.

[6] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. *International Journal of Computer Vision*, 88(2):303–338, June 2010.

[7] Theodoros Evgeniou and Massimiliano Pontil. Regularized multi–task learning. In *ACM SIGKDD*, 2004.

[8] L. Fei-Fei, R. Fergus, and P. Perona. A bayesian approach to unsupervised one-shot learning of object categories. In *International Conference on Computer Vision*, 2003.

[9] L. Fei-Fei, R. Fergus, and P. Perona. Learning generative visual models from few training examples: an incremental bayesian approach tested on 101 object categories. In *IEEE. Workshop on GMBV*, 2004.

[10] P.F. Felzenszwalb, R.B. Girshick, D. McAllester, and D. Ramanan. Object detection with discriminatively trained part-based models. *TPAMI*, 32(9):1627 –1645, 2010. ISSN 0162-8828. doi: 10.1109/TPAMI.2009.167.

[11] R. Fergus, H. Bernal, Y. Weiss, and A. Torralba. Semantic label sharing for learning with many categories. In *European Conference on Computer Vision*, 2010.

[12] Jerome Friedman, Trevor Hastie, , and Robert Tibshirani. A note on the group lasso and a sparse group lasso. *Technical report, Department of Statistics, Stanford University*, 2010.

[13] D.M. Gavrila and J. Giebel. Virtual sample generation for template-based shape matching. In *Computer Vision and Pattern Recognition*, 2001.

[14] S. Krempp, D. Geman, and Y. Amit. Sequential learning of reusable parts for object detection. Technical report, CS Johns Hopkins, 2002.

[15] C.H. Lampert, H. Nickisch, and S. Harmeling. Learning to detect unseen object classes by between-class attribute transfer. In *Computer Vision and Pattern Recognition*, 2009.

[16] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, November 1998.

[17] K. Levi, M. Fink, and Y. Weiss. Learning from a small number of training examples by exploiting object categories. In *Workshop of Learning in Computer Vision*, 2004.

[18] Joseph J. Lim, Ruslan Salakhutdinov, and Antonio Torralba. Transfer learning by borrowing examples for multiclass object detection. In *Neural Information Processing Systems (NIPS)*, 2011.

[19] E. Miller, N. Matsakis, and P. Viola. Learning from one example through shared densities on transforms. In *Computer Vision and Pattern Recognition*, 2000.

[20] A. Opelt, A. Pinz, and A. Zisserman. Incremental learning of object detectors using a visual shape alphabet. In *Computer Vision and Pattern Recognition*, 2006.

[21] A. Quattoni, M. Collins, and T.J. Darrell. Transfer learning for image classification with sparse prototype representations. In *Computer Vision and Pattern Recognition*, 2008.

[22] B. C. Russell, A. Torralba, K. P. Murphy, and W. T. Freeman. LabelMe: a database and web-based tool for image annotation. *Intional Journal of Computer Vision*, 77(1-3):157–173, 2008.

[23] R. Salakhutdinov, A. Torralba, and J. Tenenbaum. Learning to share visual appearance for multiclass object detection. In *Computer Vision and Pattern Recognition*, 2011.

[24] J. Sivic, B.C. Russell, A. Zisserman, W.T. Freeman, and A.A. Efros. Unsupervised discovery of visual object class hierarchies. In *Computer Vision and Pattern Recognition*, 2008. doi: 10.1109/CVPR.2008.4587622.

[25] E. Sudderth, A. Torralba, W. T. Freeman, and W. Willsky. Learning hierarchical models of scenes, objects, and parts. In *ICCV*, 2005.

[26] T. Tommasi, F. Orabona, and B. Caputo. Safety in numbers: Learning categories from few examples with multi model knowledge transfer. In *Computer Vision and Pattern Recognition*, 2011.

[27] A. Torralba and A. Efros. Unbiased look at dataset bias. In *Computer Vision and Pattern Recognition*, 2011.

[28] A. Torralba, K. P. Murphy, and W. T. Freeman. Sharing features: efficient boosting procedures for multiclass object detection. In *Computer Vision and Pattern Recognition*, 2004.

[29] Gang Wang, David Forsyth, and Derek Hoiem. Comparative object similarity for improved recognition with few or no examples. In *Computer Vision and Pattern Recognition*, 2010.

[30] Jianxiong Xiao, James Hays, Krista A. Ehinger, Aude Oliva, and Antonio Torralba. Sun database: Large-scale scene recognition from abbey to zoo. In *Computer Vision and Pattern Recognition*, 2010. ISBN 978-1-4244-6984-0. doi: http://doi.ieeecomputersociety.org/10.1109/CVPR.2010.5539970.

[31] Ming Yuan and Yi Lin. Model selection and estimation in regression with grouped variables. *Journal of the Royal Statistical Society, Series B*, 68:49–67, 2006.