Training Set Selection for Image Classification

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Background

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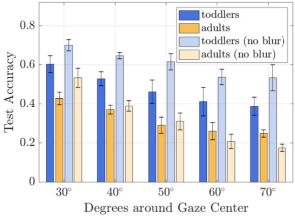
- **Goal**: Determine a training set sampling method to select the best possible images under a fixed training set size
- Largely based on "Toddler-Inspired Visual Object Learning" by Bambach, Crandall, Smith, and Yu (2018)

Background: "Toddler-Inspired Visual Object Learning"

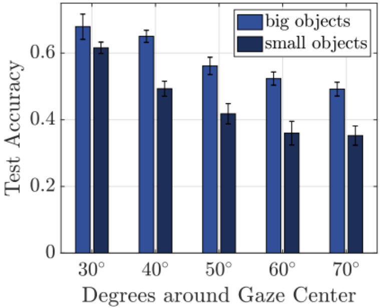
- Compared images taken by first-person cameras mounted on toddlers and parents
- Training VGG16 using toddler data resulted in higher test accuracy than training on parent data (same test set in both cases)

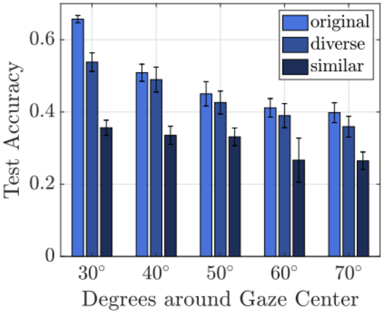


Background: “Toddler-Inspired Visual Object Learning”

- Objects in images from the toddler sample occupied more of the frame compared to objects in images from the adult sample
- Toddler
- Distilled the differences in the datasets into two components: object size (how much of the image does the object take up) and image “diversity” (hard to measure)
- Subsampled the images to obtain training subsets of:
    - big objects
    - small objects
    - diverse subset
    - similar subset
    - random subset
- Image similarity/distance based on an image embedding (GIST features)
- Found that when objects are larger or when images are more

Background: “Toddler-Inspired Visual Object Learning”





Outline and Summary

1. Applying the Toddler study to additional datasets

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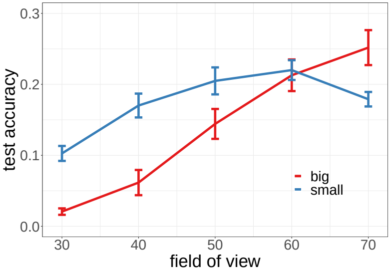
2. Some other ways to select training sets
3. Conclusions and future work

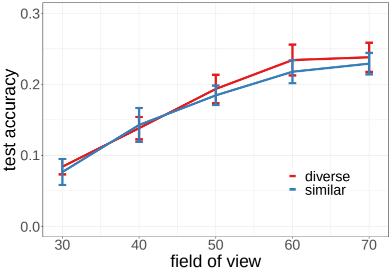
Reproduction Study: Stanford Dogs dataset

- ~20,000 images of 120 dog breeds
- 100 images per breed set aside for training
  - further subdivided into 50-50 big/small or diverse/similar
- 25 images per breed set aside for validation
- Remainder for testing

Reproduction Study: Stanford Dogs dataset

- Some evidence that object size affects training
- No significant evidence that image diversity affects training





Reproduction Study: CIFAR-10

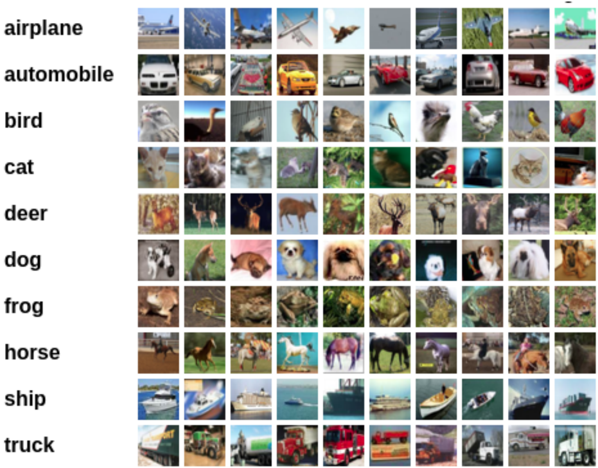
CIFAR-10

- 32×32 RGB images of 10 different object classes
- 5,000 training and 1,000 testing images per class
- No bounding box information
  - Diversity experiment only
  - No adjusting field of view

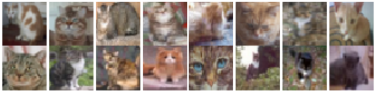
Sampling method

1. Choose training size n
2. Draw $2n$ images using diverse, similar, or random sampling
3. Split the data in half for training and validation
4. Fit VGG16 and assess accuracy on the test set

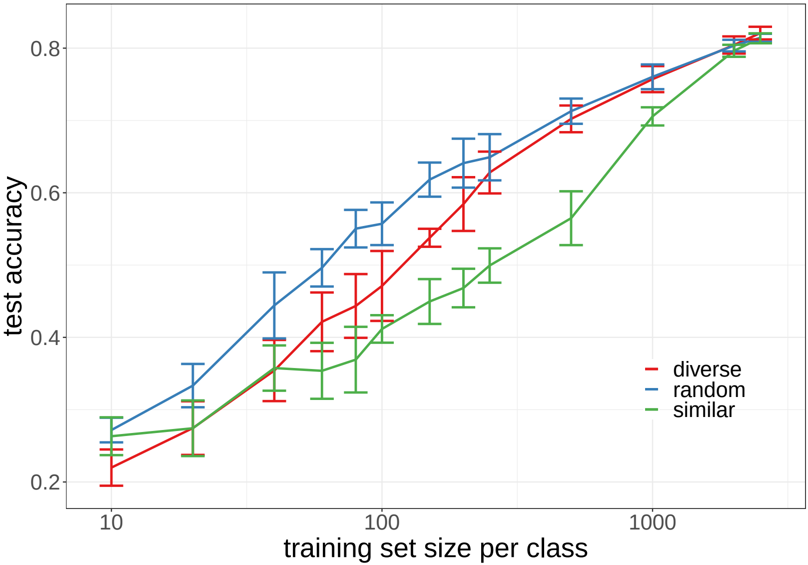
Reproduction Study: CIFAR-10



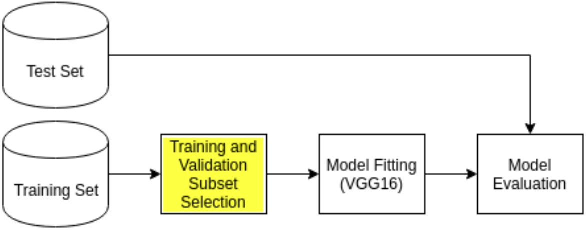
Diverse vs. Similar vs. Random Samples of CIFAR-10 Cats



Replication Study: CIFAR-10



New Approaches to Training Set Selection



Wilson Editing

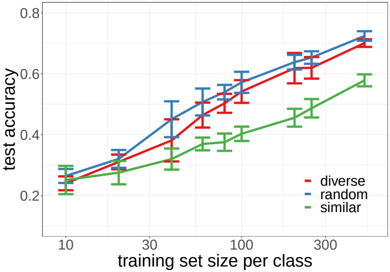
- Originally developed for k-nearest neighbors
- Algorithm
  1. Start with a sample $X_1, ..., X_n \in \mathbb{R}^p$ and corresponding discrete labels $Y_1, ..., Y_n \in \{1, ..., q\}$
  2. For $i = 1, ..., n$, determine $\hat{Y}_i$ using leave-one-out cross-validated k-nearest neighbors classification
  3. Discard $i \in \{1, ..., n\}$ where $Y_i \neq \hat{Y}_i$ to construct a reduced, "edited" training set
  4. Use the edited training set to fit a new k-nearest neighbors model
- Outperforms "unedited" k-nearest neighbors (comparing risk on a held-out test set)

Wilson Editing

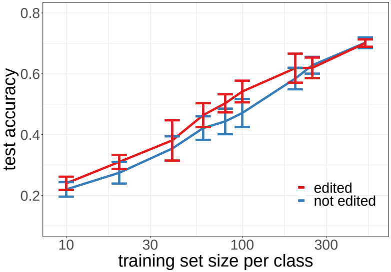
- Algorithm
  1. Use Wilson editing (using the GIST embedding) to reduce the training set
  2. For a training size n, draw a diverse sample from the edited training set
  3. Fit VGG16 on the diverse, edited training subset
  4. Assess model performance on the test set
- Idea: Draw a diverse sample while excluding "outliers"

Wilson Editing

Editing done prior to drawing diverse samples



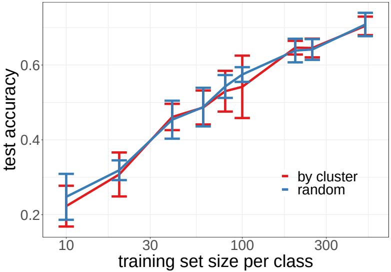
Effect of editing prior to drawing diverse samples



Clustering

Algorithm

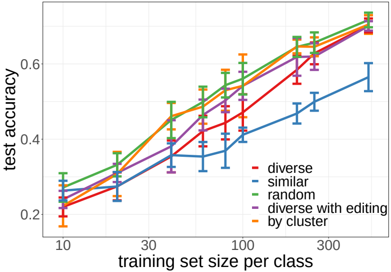
1. Use k-means clustering (using the GIST embedding) to split each class into "subclasses"
2. For a training size n, draw a cluster/subclass-stratified sample
3. Fit VGG16 on the stratified training subset
4. Assess model performance on the test set



Summary and Conclusions

- Diverse sampling outperforms similar sampling but fails to improve upon uniform random sampling
- Removing outlier images prior to drawing a diverse sample seems to improve model performance
- Cluster-stratified sampling resulted in equivalent model performance as uniform random sampling
- Future work
  - More sophisticated clustering methods
  - Active learning based approaches

Comparison of sampling methods



Supplemental Slides

VGG16

GIST Embedding

Autoencoders

Transfer Learning

- CNNs can be thought of as supervised image embedding methods
  - Second to last layer should be a linearly separable embedding
- Pretrained Xception model ($\sim$80% accuracy on CIFAR-10)
  - Xception embedding results in $\sim$80% accuracy using k-NN
  - Can be thought of as an ideal case for embedding CIFAR-10
- Diverse sampling on Xception embedding still results in worse performance than random sampling