PROBLEM STATEMENT

Problem: There's limited theoretical understanding of how model size, data size, and compute affect performance.

Research Goal: Empirically and theoretically characterize scaling laws in vision similar to those in NLP.

Approaches: Power-law fitting, scaling law estimation, empirical studies with varied model/data sizes.

Benchmark: ImageNet subsets.

INTRODUCTION

Scaling laws explain how model performance changes with increasing model size, dataset size, or compute.
They typically follow a power-law relation:

$$L = k \cdot N^{-\alpha}$$

where L is loss, N is scale (like parameters or data) and α is the scaling exponent.
In simple terms ,as we scale up models or data, the loss decreases in a predictable trend until it plateaus.
This concept helps identify how far scaling remains beneficial and when returns start diminishing.

DATASET DESCRIPTION

Source: All experiments were conducted using ImageNet subsets derived from a single class – n01494475 (tench, a species of fish).
Using a single class helps eliminate label imbalance and focus purely on the effects of model size and dataset size on performance.

Setup:
Two independent experiments were performed using different dataset configurations:

Model Loss Analysis:
Used 200 images from the class n01494475.
Purpose: To study how ResNet model depth (ResNet18, ResNet50, ResNet101) affects loss on a fixed dataset.

Dataset Loss Analysis:
Used three datasets of increasing size:
100 images → IDs 1–100
200 images → IDs 1–200
300 images → IDs 1–300

Purpose: To analyze how dataset size influences model performance and loss scaling trends.

TOOLS AND FRAMEWORKS

- **Programming Language:** Python 3.x – primary language for data handling, model training, and analysis.
- **Deep Learning Framework:** PyTorch – for loading pretrained ResNet models, customizing layers, and training.

Computer Vision Libraries:

- **OpenCV –** for image preprocessing, grayscale conversion, and contour detection.
- **PIL (Pillow) –** for image loading and basic transformations.
- Pretrained Models: ResNet18, ResNet50, ResNet101 from torchvision.models, pretrained on ImageNet.
- **Segmentation/Object Detection:** SAM (Segment Anything Model) – used for automatic region detection in images.

Data Handling and Analysis:

- **pandas –** for CSV creation and storage of per-image/model/dataset losses.
- **NumPy –** array operations and numerical computations.
- **Matplotlib and Seaborn –** for loss distributions, correlations, and scaling law plots.

OBJECT DETECTION PIPELINE

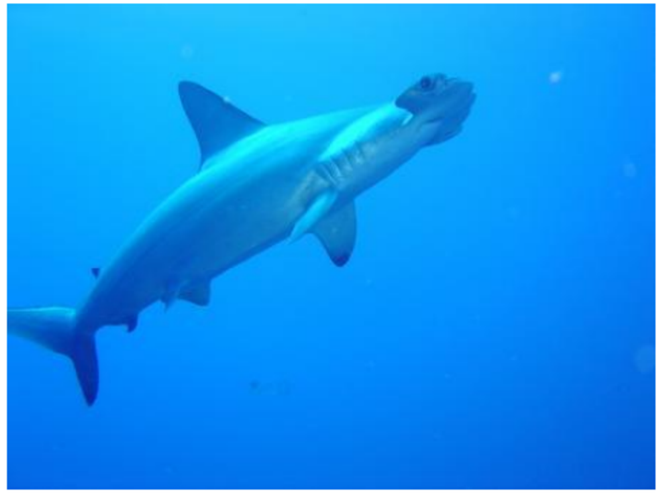
- Segment Anything Model (ViT-B) used for image segmentation.
- Each input image undergoes preprocessing before segmentation.
- Otsu’s thresholding applied to detect object regions automatically.
- Morphological operations (open, close) used to refine binary masks.
- HSV-based filtering ensures color-level region detection.
- Fallback points guarantee segmentation even in low-feature images.

Input Image → Preprocessing → Blob Detection → SAM Segmentation → Mask Output

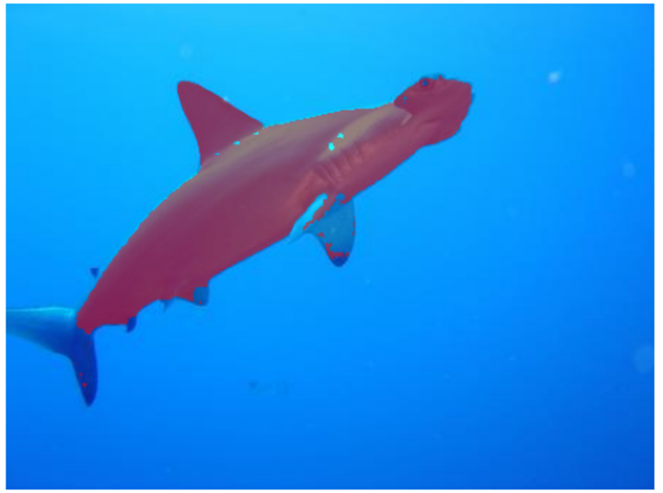
```python
def detect_blobs_otsu(gray):
    _, thresh = cv2.threshold(gray, 0, 255, cv2.THRESH_BINARY_INV + cv2.THRESH_OTSU)
    kernel = np.ones((3,3), np.uint8)
    cleaned = cv2.morphologyEx(thresh, cv2.MORPH_OPEN, kernel, iterations=2)
    merged = cv2.morphologyEx(cleaned, cv2.MORPH_CLOSE, kernel, iterations=2)
    contours, _ = cv2.findContours(merged, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    points = []
    for cnt in contours:
        area = cv2.contourArea(cnt)
        perimeter = cv2.arcLength(cnt, True)
        circularity = 4 * np.pi * area / (perimeter**2 + 1e-6)
        if MIN_AREA < area < MAX_AREA and 0.5 < circularity < 1.5:
            M = cv2.moments(cnt)
            if M["m00"] != 0:
                cx = int(M["m10"]/M["m00"])
                cy = int(M["m01"]/M["m00"])
                points.append((cx, cy))
    return points
```

```python
def detect_blobs_hsv(image):
    hsv = cv2.cvtColor(image, cv2.COLOR_RGB2HSV)
    lower = np.array([0, 50, 50])
    upper = np.array([179, 255, 255])
    mask = cv2.inRange(hsv, lower, upper)
    kernel = np.ones((3,3), np.uint8)
    cleaned = cv2.morphologyEx(mask, cv2.MORPH_OPEN, kernel, iterations=1)
    contours, _ = cv2.findContours(cleaned, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)
    points = []
    for cnt in contours:
        area = cv2.contourArea(cnt)
        if MIN_AREA < area < MAX_AREA:
            M = cv2.moments(cnt)
            if M["m00"] != 0:
                cx = int(M["m10"]/M["m00"])
                cy = int(M["m01"]/M["m00"])
                points.append((cx, cy))
    return points
```

Input Image



Segmented Overlay



LOSS CALCULATION

Different loss functions were considered, but MSE was chosen as the most suitable for analyzing scaling behavior.

- Cross-Entropy Loss: Designed for classification tasks; outputs discrete probability distributions. Not meaningful for continuous pixel or feature-level comparisons.
- MAE (Mean Absolute Error): Treats all deviations equally; less sensitive to large errors and produces less distinct scaling patterns.
- Huber Loss: Hybrid of MSE and MAE, robust but adds unnecessary complexity since outliers weren’t dominant in our data.
- MSE (Mean Squared Error): Best suited for continuous-valued regression; penalizes large deviations more, offering a clearer quantitative measure of model performance relative to scale.

MODEL LOSS COMPUTATION PIPELINE

Dataset Handling:

- Images are loaded from a single folder (200Images) and preprocessed to 224×224 using PyTorch transforms.
- A custom Dataset class ensures numeric sorting of filenames for reproducibility.

Model Preparation:

- Three ResNet architectures (ResNet18, ResNet50, ResNet101) are loaded with pretrained ImageNet weights.
- All layers are frozen except the fully connected (FC) layer.
- The FC layer is modified to output a vector of the same size as input, acting like an identity mapping.

Training Strategy:

- Only the FC layer is trained for a few epochs using Mean Squared Error (MSE) loss.
- MSE is used here because it provides a scalar measure of the difference between the FC output and its target, suitable for creating a uniform per-image metric across models.
- Purpose: generate “pre-loss” values representing model-specific output magnitudes per image, without affecting pretrained features.

Logging Losses:

- After training, the MSE values are computed per image for each model.
- Stored in a dictionary and exported to CSV for subsequent scaling law analysis.
- Provides a consistent metric to compare performance across models and support empirical study of scaling laws.

```
for model_name in models_to_run:
    print(f"\nTraining {model_name}...")
    model = get_model(model_name)
    optimizer = torch.optim.Adam(model.fc.parameters(), lr=learning_rate)
    criterion = nn.MSELoss()

    # Training FC layer
    for epoch in range(num_epochs):
        for inputs, _ in dataloader:  # labels not used
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, outputs.detach())  # dummy backward to train FC
            loss.backward()
            optimizer.step()
```

DATASET LOSS COMPUTATION PIPELINE

Dataset Handling:

- Three datasets are used, created from ImageNet subsets: 100, 200, and 300 images.
- Images are preprocessed to 224×224 using PyTorch transforms.
- Images are sorted numerically/alphabetically to maintain consistent ordering.

Model Preparation:

- ResNet18 is loaded with pretrained ImageNet weights.
- All layers are frozen except the fully connected (FC) layer.
- The FC layer is modified to output a vector of size 512, providing a uniform representation for loss computation.

Training Strategy:

- Only the FC layer is trained for a few epochs using Mean Squared Error (MSE) loss.
- MSE is chosen because it provides a scalar measure of difference between the FC output and input vector, creating a consistent per-image metric across datasets.
- Purpose: generate per-image loss values for each dataset size, while keeping pretrained features intact.

Logging Losses:

- After training, the MSE loss for each image is computed and logged for each dataset size.
- Data is stored in a CSV with columns: image_name, loss_100, loss_200, loss_300.
- These values serve as the dataset-specific loss metric for scaling law analysis.

```
resnet18 = models.resnet18(weights=models.ResNet18_Weights.IMAGENET1K_V1)
for param in resnet18.parameters():
    param.requires_grad = False
resnet18.fc = nn.Linear(resnet18.fc.in_features, 512)

criterion = nn.MSELoss()
optimizer = optim.SGD(resnet18.fc.parameters(), lr=0.001)
```

```
try:
    output_vec = resnet18(input_vec)
    loss_val = criterion(output_vec.view(-1), input_vec.view(-1)[:output_vec.numel()])
    loss_val.backward()
    optimizer.step()
except Exception as e:
    print(f"Error processing {img_name}: {e}")
    loss_val = None
```

EMPIRICAL OBSERVATIONS

- Model depth impacts per-image loss: ResNet50 and ResNet101 generally show lower median and maximum losses than ResNet18.
- Dataset scaling shows minimal aggregate effect: loss slightly increases with larger datasets ($\alpha \approx -0.02$), but per-image variability is significant.
- Correlation analysis: deeper models (ResNet50 vs ResNet101) are highly correlated, whereas correlation across dataset sizes is weaker.
- Scaling exponents highlight trends: negative α for model depth suggests possible overfitting on smaller datasets; near-zero α for dataset size indicates minimal scaling impact.
- Per-image variations emphasize need for targeted optimization: preprocessing or selective data augmentation could improve outcomes.

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