

Adapting Models to Signal Degradation using Distillation



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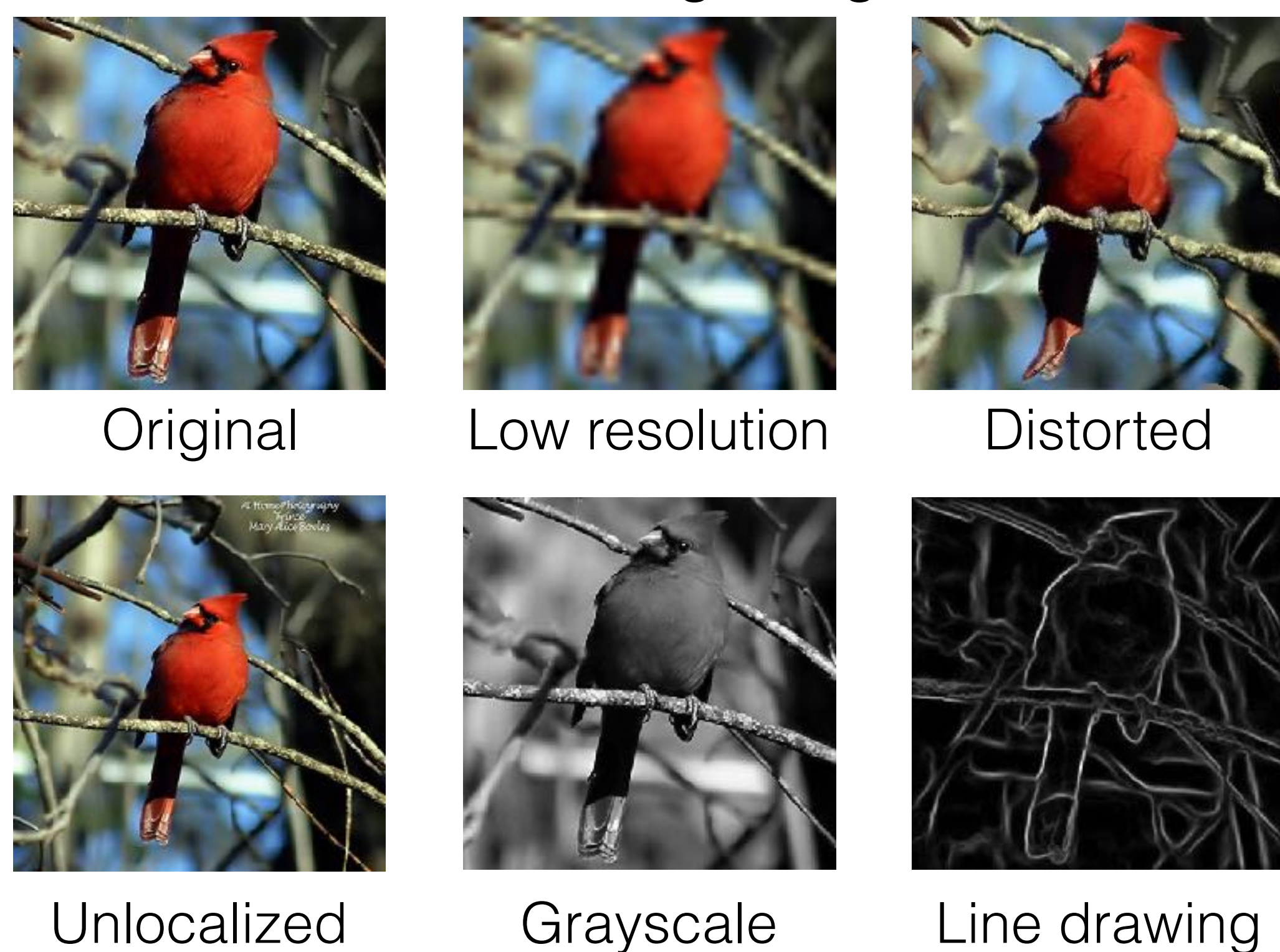


Motivation

Convolutional neural networks are effective at several visual recognition tasks. However, they are prone to the degradation of image quality.



Various forms of image degradation:

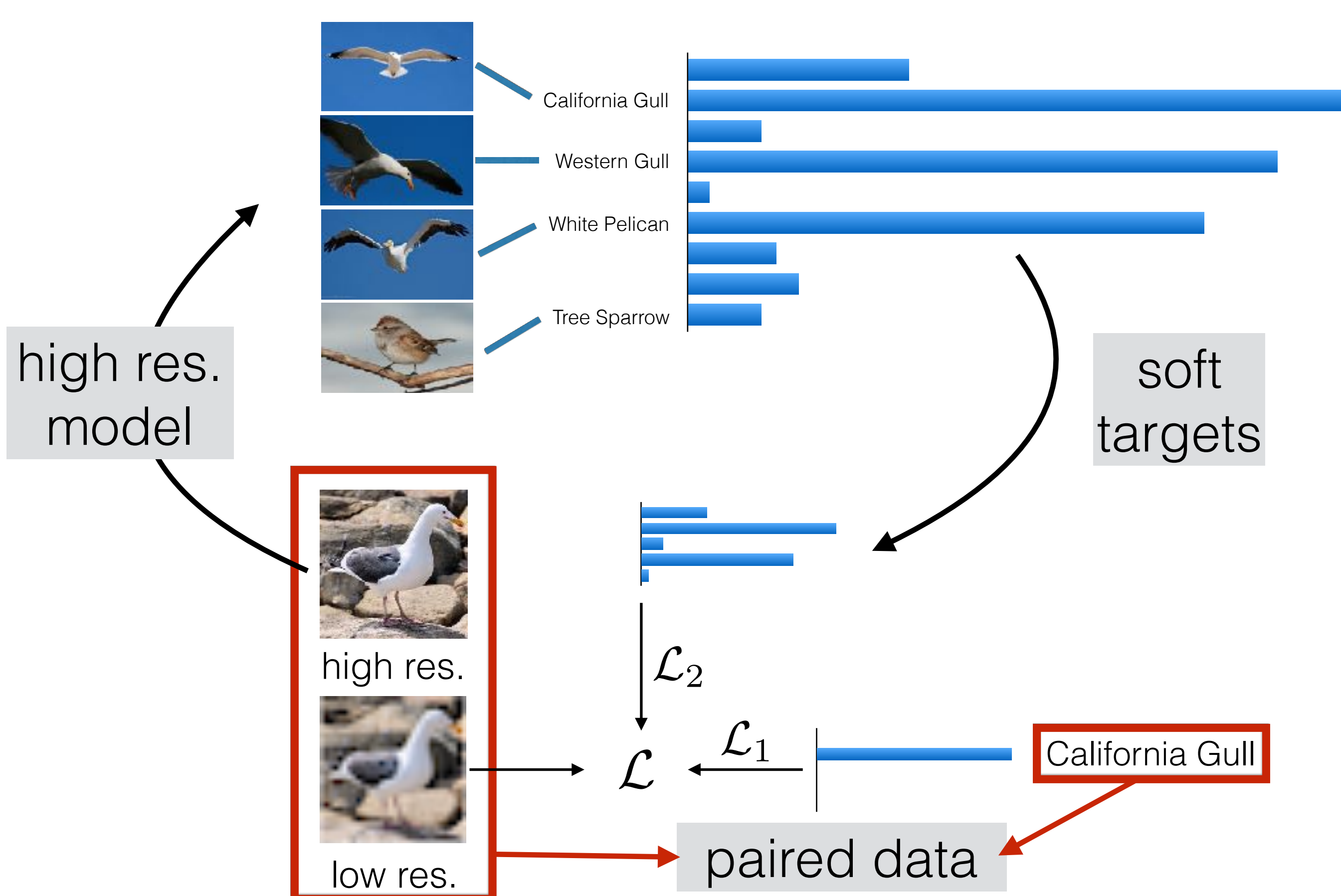


Prior Work

- Problem-specific solutions
 - Super-resolution, Image colorization, etc.
- Domain adaptation
 - DSLR \leftrightarrow webcam images, high \leftrightarrow low resolution images
- Transfer learning
 - ImageNet \leftrightarrow CUB low resolution data

Our Approach

- **Cross Quality Distillation (CQD)**
- **Assumption:** “paired” training data is available
 1. Train a model on high quality data
 2. Train a model on the low quality data to match:
 - (1) The target labels
 - (2) The “soft targets” produced by the first model



Soft targets provide more information per example leading to better knowledge transfer across domains [1, 2]

References

- [1] Distilling knowledge in a neural network. G. Hinton, O. Vinyals, and J. Dean, *Deep Learning and Representation Learning Workshop, NIPS*, 2014.
- [2] Model compression. C. Buciluă, R. Caruana, and A. Niculescu-Mizil, *SIGKDD*, 2006.

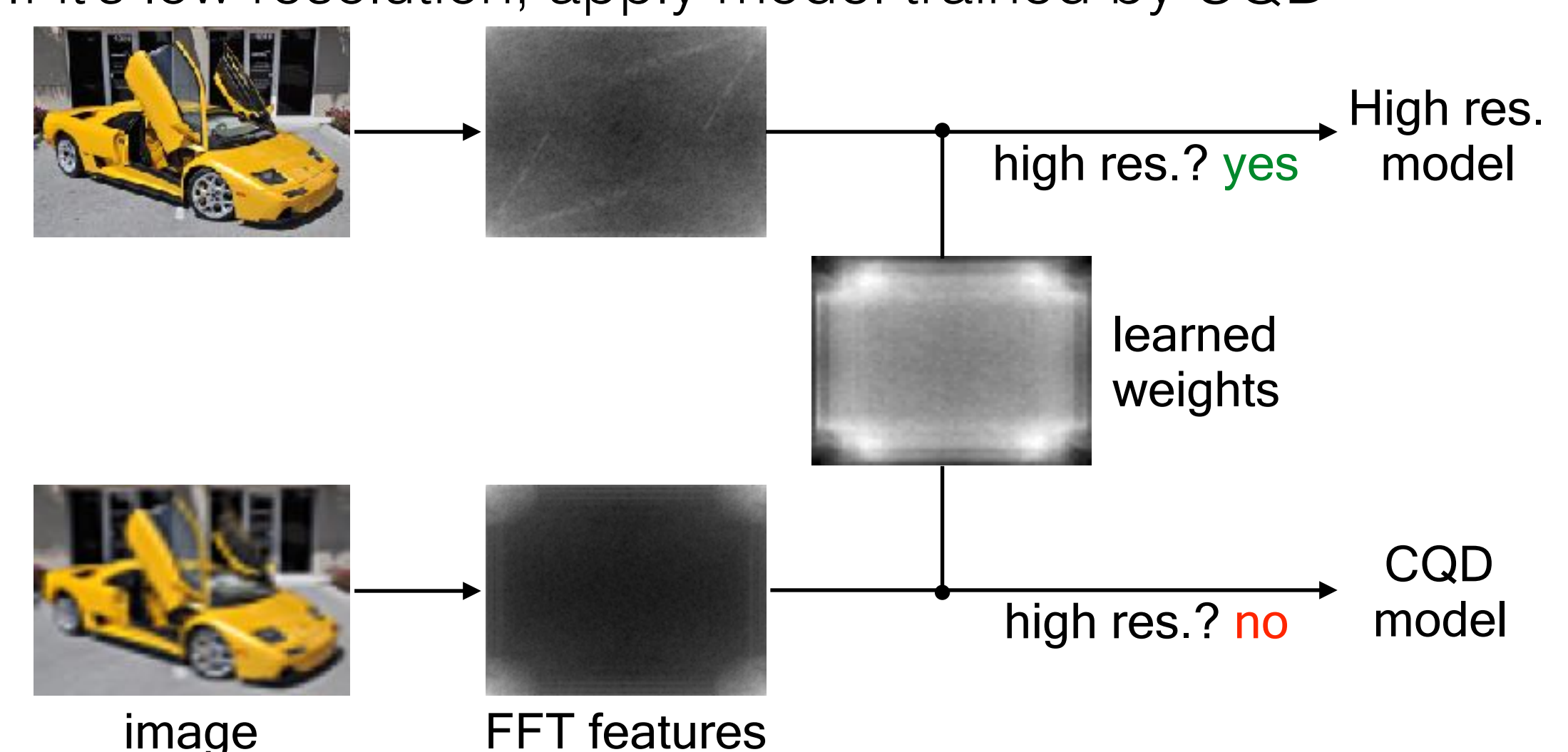
Results

Accuracy on CUB low quality dataset

| Model | Localization | Low resolution | Line drawing | Local. + low res. |
|-------------------|--------------|----------------|--------------|-------------------|
| Oracle | 67.0 | 67.0 | 67.0 | 67.0 |
| No adaptation | 57.4 | 39.4 | 1.9 | 24.9 |
| Fine-tuning | 60.8 | 61.0 | 29.2 | 46.2 |
| Data augmentation | 63.6 | 62.2 | 32.5 | 51.7 |
| Staged training | 62.4 | 62.3 | 30.4 | 50.4 |
| CQD | 64.4 | 64.4 | 34.1 | 52.7 |

Multi-Resolution Model

1. Train a model to predict image quality.
2. For each image:
 - (1) If it's high resolution, apply model trained on high res. data
 - (2) If it's low resolution, apply model trained by CQD



| Model | Test on high res. | Test on low res. | Test on high res. + low res. |
|-------------------------------|-------------------|------------------|------------------------------|
| Train on high res. data | 59.3 | 7.6 | 33.5 |
| CQD | 31.8 | 48.8 | 40.3 |
| Train on high res. + low res. | 57.3 | 47.3 | 52.3 |
| Multi-resolution | - | - | 54.0 |
| Oracle | 59.3 | 48.8 | 54.1 |

Multi-resolution model is better than using one model trained on high res. + low res. data.

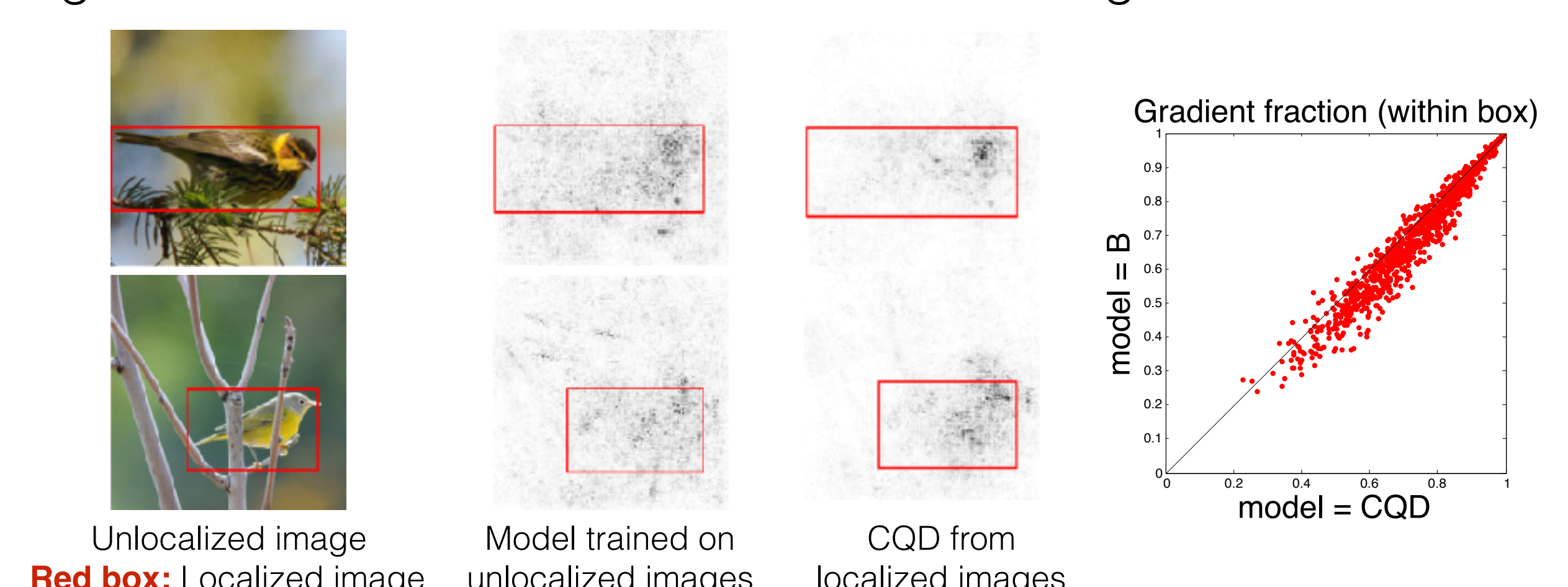
Distillation and Model Compression

A deeper CNN trained on high-quality data can be distilled to a shallow CNN trained on low-quality data.

| Model distilled from \rightarrow to | Training \rightarrow Testing | | | A: CUB localized B: CUB unlocalized |
|---------------------------------------|--------------------------------|-------------------|---------------------|--|
| | A \rightarrow A | B \rightarrow B | CQD \rightarrow B | |
| VGG-m \rightarrow VGG-m | 67.0 | 60.8 | 63.7 | |
| VGG-16 \rightarrow VGG-m | - | - | 64.6 | |
| VGG-16 \rightarrow VGG-16 | 74.9 | 69.5 | 72.4 | |

Visualization

We visualize the gradient of an image w.r.t. true class label. By distilling from localized images to unlocalized images, the gradient is more focused inside the bounding-boxes.



Distillation from a localized image can help us localize the object on an unlocalized image.