Investigating Data Augmentation Strategies for Advancing Deep Learning Training

如何準備深度學習必須的訓練資料？

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PI & Director, NVIDIA AI Lab
National Taiwan University

May 30, 2018
Advanced Research and Industrial Collaborations (2007~)
Outline

- Why data augmentation in deep learning?
- Data augmentation strategies by
  - Data crawling
  - Weakly (or semi-) supervised learning (least effort for data)
  - Data transformation
  - Synthesizing
- Summary
Observations in GTC 2018 (San Jose) – Focusing on Realizing Neural Networks into Products

- Lecturing a 50min talk – **Investigating Data Augmentation Strategies for Advancing Deep Learning Training**
  - Fully packed (and overflowed) in a 150-seat lecture room (**9am, Monday, March 26**)
Deep Learning – a Paradigm Shift in Machine Learning

- Competitive “deep” neural network
- Automatic feature learning (convolution)
- Huge improvements in image/video recognition tasks; so do in audio/speech applications; but marginally in text analytics
- For example, classification track in ILSVRC (Top 5 Error)

<table>
<thead>
<tr>
<th>Year</th>
<th>Team</th>
<th>Result</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>SuperVision</td>
<td>0.15</td>
<td>1st Place (CNN)</td>
</tr>
<tr>
<td>2012</td>
<td>ISI</td>
<td>0.26</td>
<td>2nd Place (Conventional)</td>
</tr>
<tr>
<td>2015</td>
<td>MSRA</td>
<td>0.036</td>
<td>1st Place (CNN)</td>
</tr>
</tbody>
</table>

*over 96% accuracy if 5 guesses are provided*
Why Deep Neural Networks So Powerful?

- “End-to-end training” by
  - Huge training data, GPUs, advanced algorithms, etc.

![Diagram showing the process of deep neural networks with training image, weights, and training label.](image)
Deficiencies in Convolutional Neural Networks for Industry Products

- huge training data required, collected manually now
- proper network structures?
- multimodal data ignored
- bulky parameters & computations

Feature Extraction & Learning (CNN)

Prediction
Data is Vital across Learning Paradigms – Example via the (Old) Computer Vision Methods

- PASCAL VOC detection challenge provides realistic benchmark of object detection performance

Zhu et al. Do We Need More Training Data or Better Models for Object Detection? BMVC 2012
Data is Vital for Deep Learning

▪ AI algorithm is biased?

▪ Story covered in “Facial Recognition Is Accurate, if You’re a White Guy,” The New York Times, Feb. 9, 2018

▪ Actually, “gender classification” error caused by lacking quality data in certain categories
  – e.g., the darker the skin, the more errors arise
  – More specific training data will help

▪ Also explained in my Digitimes columns

Where/How to Get Quality Training Data in an Efficient and Effective Way?

\[ X \rightarrow \Theta \rightarrow Y \]

- Training data
- Training label
- "dog"
- Backpropagation
1 Data Crawling
Rich Image/Videos, Comments, Metadata (GPS, Tags, Time, etc.) in Social Media

Why? Sharing for organization and social communication
[Ames, et al., CHI’07]
The First AI-Generated Movie Trailer – Learning from Hundreds of (Horror) Trailers

[Smith et al., ACM MMM’17]

Image to Poetry by Cross-Modality Understanding

- Joint work with Microsoft Research Asia; deployed live in Microsoft chatbot Xiaolce (小冰)

- Learning from the 519 poets (1920~)

- Hierarchical LSTM-like models for ensuring the intra- and inter-sentence coherence
Netizen-Style Commenting by Learning from Fashion Communities – NetiLook (Public) Dataset

- Netizen-style commenting → human like chatting with diverse wordings/emojis

- Contributing the first (large-scale) clothing dataset named **NetiLook** to discover netizen-style comments; **355,205** images from **11,034** users and **5 million** associated comments collected from Lookbook.

- Investigating commenting diversity by topic-parameterized neural networks (NSC)

---

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Images</th>
<th>Sentences</th>
<th>Average Length</th>
<th>Unique Words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flickr30k</td>
<td>30K</td>
<td>150K</td>
<td>13.39</td>
<td>23,461</td>
</tr>
<tr>
<td>MS COCO</td>
<td>200K</td>
<td>1M</td>
<td>10.46</td>
<td>54,231</td>
</tr>
<tr>
<td>NetiLook</td>
<td>350K</td>
<td>5M</td>
<td>3.75</td>
<td>597,629</td>
</tr>
</tbody>
</table>
Social Media are Noisy and Biased

- Subjective and inaccurate for social tagging [Chang, 08]

<table>
<thead>
<tr>
<th>Locations</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brooklyn Br.</td>
<td>0.38</td>
</tr>
<tr>
<td>Chrysler Building</td>
<td>0.65</td>
</tr>
<tr>
<td>Columbia University</td>
<td>0.30</td>
</tr>
<tr>
<td>Empire State Building</td>
<td>0.18</td>
</tr>
</tbody>
</table>

- Bias in many aspects: gender, word length, freq, etc. (e.g., NetiLook Dataset)

Locations Precision
- Brooklyn Br. 0.38
- Chrysler Building 0.65
- Columbia University 0.30
- Empire State Building 0.18

New York Landmark Labels (Flickr)

- Longest: 1,314
- Avg: 3.78

Unknown Female Male

277 1739 2366
Data Annotation – Gaming with a Purpose

- **ESP Game**: labeling image as games [von Ahn, SIGCHI’04]
  - Two people see the same image, and type keywords until they match

- **Other variants**:
  - PeekABoom, Google Labeler, and more in www.gwap.com
  - Label Me
Data Annotation – Advanced Approaches

- Information beyond images/videos
  - speech, semantic network, location, hybrid tag/browse and … mind-reading

Speech Recognition

http://www.expertsystem.net

Yahoo! ZoneTag

Brain-Computer Interface
(Pic. From www.ice.hut.fi)

Hybrid Tag-Browse Labeler
[Yan et al., 2008]
Data Annotation – Outsourcing Labeling Task

- **Goal** – outsourcing tasks to a distributed group of people
  - to share the annotation efforts
  - to reduce the personal bias

- Paid crowd-sourcing by Amazon Mechanical Turk

- **Mechanisms for ensuring quality**
  - Being completely answered in a HIT
  - Consistence for the “duplicated” questions in a HIT
  - Avoiding robots
  - ...

- Nice tutorial for annotations for numerous visual learning tasks in [Kovashka et al.]


- **Goal** – data-driven, machine learning-driven approaches are cheaper for collecting (predicting) census data (e.g., income, per capita carbon emission, crime rates, etc.) from Google Street View images

- **Dataset** – the largest fine-grained dataset reported to date consisting of over **2600 classes** of cars comprised of images from **Street View** and other **web sources**, classified by car experts and AMT (object)
“Automatically” Acquiring Effective Training Images for Learning Facial Attributes

- Challenges:
  - Noise
  - Visual diversity
  - Geographical diversity

- Goals
  - Effectiveness for general facial attributes → data/feature selection
  - More diversity in training data → enhanced by contexts

Chen et al. Automatic Training Image Acquisition and Effective Feature Selection From Community-Contributed Photos for Facial Attribute Detection. IEEE TMM 2013
Balancing Content and Context from Social Images

\[ g_k = 1 - \frac{B_G(v_k)}{|G|} \]

- \( v_k \) : votes from pseudo positives (negatives), weighted by \( x_m \)
- \( g_k \) : relative \( v_k \) in a grid

Limit the number of images from a grid

\[
\min_p \sum_k^K \left( p_k - t_k \right)^2 - \beta g_k p_k + \gamma \| p_k \|^2
\]

Textual Relevance  Visual Consistency  Regularization

\( p_k \) : annotation quality; selection indicator [0, 1]
Geographical Diversity for Training Facial Recognizers

<table>
<thead>
<tr>
<th></th>
<th>elder</th>
<th>kid</th>
<th>male</th>
</tr>
</thead>
<tbody>
<tr>
<td>Classification</td>
<td>26.33</td>
<td>18.66</td>
<td>24.50</td>
</tr>
<tr>
<td>Error Rate (%)</td>
<td>(-0.00)</td>
<td>(-0.67)</td>
<td>(-3.00)</td>
</tr>
</tbody>
</table>

without geo-context

with geo-context
2 Least Effort for the Data
Learning from Noisy Labels – Annotation is Very Expensive (1/2)

- A multi-task network that jointly learns to clean noisy annotations and to accurately classify images.

- Using the small clean dataset to learn a mapping between noisy and clean annotations (in a residual manner).

Veit at al. Learning From Noisy Large-Scale Datasets With Minimal Supervision. CVPR 2017
Learning from Noisy Labels
– Annotation is Very Expensive (2/2)

- Using the clean labels to directly fine-tune a network trained on the noisy labels does not fully leverage the information.

- Clean labels are used to reduce the noise in the large dataset before fine-tuning the network using both the clean labels and the full dataset with reduced noise.

- Experiments in Open Images dataset,
  – **Noisy set**: ~9 million images over 6000 unique classes
  – **Small clean set**: ~40k images.

<table>
<thead>
<tr>
<th>Model</th>
<th>$AP_{all}$</th>
<th>$MAP$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>83.82</td>
<td>61.82</td>
</tr>
<tr>
<td>Misra et al. [22] visual classifier</td>
<td>83.55</td>
<td>61.85</td>
</tr>
<tr>
<td>Misra et al. [22] relevance classifier</td>
<td>83.79</td>
<td>61.89</td>
</tr>
<tr>
<td>Fine-Tuning with mixed labels</td>
<td>84.80</td>
<td>61.90</td>
</tr>
<tr>
<td>Fine-Tuning with clean labels</td>
<td>85.88</td>
<td>61.53</td>
</tr>
<tr>
<td><strong>Our Approach</strong> with pre-training</td>
<td><strong>87.68</strong></td>
<td><strong>62.36</strong></td>
</tr>
<tr>
<td><strong>Our Approach</strong> trained jointly</td>
<td>87.67</td>
<td><strong>62.38</strong></td>
</tr>
</tbody>
</table>
Network in Network (NIN) – Compact Networks with Global Average Pooling

<table>
<thead>
<tr>
<th>Parameter Number</th>
<th>Performance</th>
<th>Time to train (GTX Titan)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>60 Million (230 Megabytes)</td>
<td>40.7% (Top 1)</td>
</tr>
<tr>
<td>NIN</td>
<td>7.5 Million (29 Megabytes)</td>
<td>39.2% (Top 1)</td>
</tr>
</tbody>
</table>
Global Average Pooling – Huge Parameter Saving by Removing FC Layers

- Global average pooling layer produces spatial average of feature maps as confidence of categories
- Correspondence between feature maps and categories preserved; more meaningful and interpretable.
- No parameters (compared to fully connected layers) → prevent overfitting
- Robust to spatial translations of input
Side Product for Global Average Pooling – Visualizing Learned Spatial Correspondence

1. airplane, 2. automobile, 3. bird, 4. cat, 5. deer, 6. dog, 7. frog, 8. horse, 9. ship, 10. truck
Class Activation Map for Weakly Supervised Object Localization (1/3)

- Investigating what CNN is looking in image classification
  - Global Average Pooling (GAP): (1) Does not harm classification results, (2) Remarkable localization ability
  - Class Activation Map (CAM)

Class Activation Map for Weakly Supervised Object Localization (2/3)

- The CAMs of two classes from ILSVRC. The maps highlight the discriminative image regions used for image classification, the head of the animal for “briard” and the plates in “barbell”.

![Class Activation Maps](image)
Class Activation Map for Weakly Supervised Object Localization (3/3)

### Table 2. Localization error on the ILSVRC validation set. Back-prop refers to using [23] for localization instead of CAM.

<table>
<thead>
<tr>
<th>Method</th>
<th>top-1 val.error</th>
<th>top-5 val. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogLeNet-GAP</td>
<td>56.40</td>
<td>43.00</td>
</tr>
<tr>
<td>VGGnet-GAP</td>
<td>57.20</td>
<td>45.14</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>60.09</td>
<td>49.34</td>
</tr>
<tr>
<td>AlexNet* -GAP</td>
<td>63.75</td>
<td>49.53</td>
</tr>
<tr>
<td>AlexNet-GAP</td>
<td>67.19</td>
<td>52.16</td>
</tr>
<tr>
<td>NIN</td>
<td>65.47</td>
<td>54.19</td>
</tr>
<tr>
<td>Backprop on GoogLeNet</td>
<td>61.31</td>
<td>50.55</td>
</tr>
<tr>
<td>Backprop on VGGnet</td>
<td>61.12</td>
<td>51.46</td>
</tr>
<tr>
<td>Backprop on AlexNet</td>
<td>65.17</td>
<td>52.64</td>
</tr>
<tr>
<td>GoogLeNet-GMP</td>
<td>57.78</td>
<td>45.26</td>
</tr>
</tbody>
</table>

### Table 3. Localization error on the ILSVRC test set for various weakly- and fully- supervised methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>supervision</th>
<th>top-5 test error</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogLeNet-GAP (heuristics)</td>
<td>weakly</td>
<td>37.1</td>
</tr>
<tr>
<td>GoogLeNet-GAP</td>
<td>weakly</td>
<td>42.9</td>
</tr>
<tr>
<td>Backprop [23]</td>
<td>weakly</td>
<td>46.4</td>
</tr>
<tr>
<td>OverFeat [22]</td>
<td>full</td>
<td>29.9</td>
</tr>
<tr>
<td>AlexNet [25]</td>
<td>full</td>
<td>34.2</td>
</tr>
</tbody>
</table>
Weakly Supervised Object Detection

- Usual object detector is trained by dataset annotated with bounding boxes
  - Collecting those labels can be very costly and labor intensive.
  - For fields like medical imaging, the labels are even more expensive.
  - Image-level annotation is much easier to get

- Weakly Supervised object detection
  - Aim to train the model to localize the object with only image level supervision (only class label, no bounding boxes)
Weakly Supervised Learning for Localizing Thoracic Diseases – Problem Definition

- Bounding box labels for medical images require professionals to generate the training data. It’s rather time-consuming and expensive.

- Goal – train the network to automatically localize the lesions with only image level supervision. (no bounding box info)

Wang et al., ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. CVPR 2017

Red: Ground truth bbox
Green: Predicted bbox
NIH Chest X-Ray 8 Dataset

- Training: 108,948, 8 frontal view X-ray images of 32,717 unique patients with the recording containing disease image class labels (noisy)

- 985 human annotated bounding boxes on 880 images by 8 chest pathologies

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Wang et al., ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. CVPR 2017
Baseline Proposal and Results

- A multi-label classifier with pooling layer (LSE) to increase the localize capability of the network (mixture of GAP and GMP).

- Multiply the weights from prediction layers with the conv feature map to generate the activation heatmap of a specific class, similar to CAM.
3 Data Transformation
Recent Data Augmentation Methods

- Summarized by Thoma in arXiv’17

- Further operations
  - Adding noise
  - Elastic deformations
  - Color casting
  - Vignetting
  - Lens distortion

<table>
<thead>
<tr>
<th>Name</th>
<th>Augmentation Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal flip</td>
<td>2</td>
</tr>
<tr>
<td>Vertical flip</td>
<td>2</td>
</tr>
<tr>
<td>Rotation</td>
<td>$\sim 40$ ($\delta = 20$)</td>
</tr>
<tr>
<td>Scaling</td>
<td>$\sim 14$ ($\delta \in [0.7, 1.4]$)</td>
</tr>
<tr>
<td>Crops</td>
<td>$32^2 = 1024$</td>
</tr>
<tr>
<td>Shearing</td>
<td></td>
</tr>
<tr>
<td><strong>GANs</strong></td>
<td></td>
</tr>
<tr>
<td>Brightness</td>
<td>$\sim 20$ ($\delta \in [0.5, 1.5]$)</td>
</tr>
<tr>
<td>Hue</td>
<td>51 ($\delta = 0.1$)</td>
</tr>
<tr>
<td>Saturation</td>
<td>$\sim 20$ ($\delta = 0.5$)</td>
</tr>
<tr>
<td>Contrast</td>
<td>$\sim 20$ ($\delta \in [0.5, 1.5]$)</td>
</tr>
<tr>
<td>Channel shift</td>
<td></td>
</tr>
</tbody>
</table>
Deep Image: Scaling up Image Recognition – Wu et al., arxiv, 2015 (Baidu)

- Data augmentation
  - Cropping, shifting, color casting, lens distortion, vignetting, etc.

- Training on multi-scale images, including high-resolution ones
  - 512x512 vs. 224x224

- Hardware/software co-design for parallel computation
  - The number of weights is 212.7M
  - Estimated with 1GB for parameters
Deep Image: Scaling up Image Recognition – Wu et al., arxiv, 2015 (Baidu)

- Configurations
  - 36 server nodes; each with 4 nvidia Tesla K40; FDR InfiniBand (56Gb/s)
  - Data parallelism in convolutional layers and model parallelism in FC layers
  - SGD synchronization: asynchronous updates

- Impacts

<table>
<thead>
<tr>
<th>Team</th>
<th>Year</th>
<th>Place</th>
<th>Top-5 error</th>
</tr>
</thead>
<tbody>
<tr>
<td>SuperVision</td>
<td>2012</td>
<td>1</td>
<td>16.42%</td>
</tr>
<tr>
<td>ISI</td>
<td>2012</td>
<td>2</td>
<td>26.17%</td>
</tr>
<tr>
<td>VGG</td>
<td>2012</td>
<td>3</td>
<td>26.98%</td>
</tr>
<tr>
<td>Clarifai</td>
<td>2013</td>
<td>1</td>
<td>11.74%</td>
</tr>
<tr>
<td>NUS</td>
<td>2013</td>
<td>2</td>
<td>12.95%</td>
</tr>
<tr>
<td>ZF</td>
<td>2013</td>
<td>3</td>
<td>13.51%</td>
</tr>
<tr>
<td>GoogLeNet</td>
<td>2014</td>
<td>1</td>
<td>6.66%</td>
</tr>
<tr>
<td>VGG</td>
<td>2014</td>
<td>2</td>
<td>7.32%</td>
</tr>
<tr>
<td>MSRA</td>
<td>2014</td>
<td>3</td>
<td>8.06%</td>
</tr>
<tr>
<td>Andrew Howard</td>
<td>2014</td>
<td>4</td>
<td>8.11%</td>
</tr>
<tr>
<td>DeeperVision</td>
<td>2014</td>
<td>5</td>
<td>9.51%</td>
</tr>
<tr>
<td>Deep Image</td>
<td>-</td>
<td>-</td>
<td>5.98%</td>
</tr>
</tbody>
</table>

Table 4: Single model comparison.

<table>
<thead>
<tr>
<th>Team</th>
<th>Top-1 val. error</th>
<th>Top-5 val. error</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogLeNet [21]</td>
<td>7.89%</td>
<td></td>
</tr>
<tr>
<td>VGG [20]</td>
<td>25.9%</td>
<td>8.0%</td>
</tr>
<tr>
<td>Deep Image</td>
<td>24.88%</td>
<td>7.42%</td>
</tr>
</tbody>
</table>

Figure 4: Validation set accuracy for different numbers of GPUs.
Industry Example – Image Recognition for Consumer Photo Management by Synology Inc. (1/2)

- Securing **robustness** in recognizing consumer photos, often suffering from varying lighting conditions

![Comparison of image recognition with and without augmentation](image)

- **w/o augmentation**
  - Confidence score for label “beach”
  - w/o augmentation: 49.2832%, 94.6000%, 80.1941%

- **w/ augmentation**
  - Confidence score for label “beach”
  - w/ augmentation: 99.9953%, 99.9958%, 99.9941%
Industry Example – Image Recognition for Consumer Photo Management by Synology Inc. (2/2)

- Random flip, random crop
- Python open source image augmentation library: **imgaug**
  - Using blur, gaussian noise, brightness, hue, contrast and gray scale
“Shrinking Image” for Learning Super-Resolution (or Face Hallucination)

- 1/16 or 1/64 size of the original (high quality) one for measuring the reconstruction quality (pixel level or perceptual level)
- Mostly with encoder-decoder structure

- Deep Laplacian Pyramid Networks for Fast and Accurate Super-Resolution. CVPR 2017
- Dong et al. Accelerating the Super-Resolution Convolutional Neural Network. ECCV 2016

[Zhang et al., 2018]
“Simulated Blurred Images” for Learning De-blurring

- Simulated blurred data from the original (high quality) one

- Gong et al., From Motion Blur to Motion Flow: a Deep Learning Solution for Removing Heterogeneous Motion Blur. CVPR 2017
- Liang et al., Dual Motion GAN for Future-Flow Embedded Video Prediction. ICCV 2017
4 Synthesizing Data
**Motivations** – labelling images for detection is time-consuming.
   – Every object must be marked with a bounding box.

**Augmenting the training data with synthetic images rendered from 3D CAD models (e.g., 3dwarehouse)**

Learning Object Detector from 3D Models (2/5)

- How variations in low-level cues affect the features by CNN on the object detection (e.g., PASCAL VOC2007 dataset).
  - Object color, texture and context
  - Synthetic image pose
  - 3D Shape
Learning Object Detector from 3D Models (3/5) – Object Color, Texture and Context

The network has learned to be invariant to the color and texture of the object and its background.

<table>
<thead>
<tr>
<th></th>
<th>RR-RR</th>
<th>W-RR</th>
<th>W-UG</th>
<th>RR-UG</th>
<th>RG-UG</th>
<th>RG-RR</th>
</tr>
</thead>
<tbody>
<tr>
<td>BG</td>
<td>Real RGB</td>
<td>White</td>
<td>White</td>
<td>Real RGB</td>
<td>Real Gray</td>
<td>Real Gray</td>
</tr>
<tr>
<td>TX</td>
<td>Real RGB</td>
<td>Real RGB</td>
<td>Unif. Gray</td>
<td>Unif. Gray</td>
<td>Unif. Gray</td>
<td>Real RGB</td>
</tr>
</tbody>
</table>

| PASC-FT |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |    mAP |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|       |
| RR-RR   | 50.9  | 57.5  | 28.3  | 20.3  | 17.8  | 50.1  | 37.7  | 26.1  | 11.5  | 27.1  | 2.4   | 25.3  | 40.2  | 52.2  | 14.3  | 11.9  | 40.4  | 16.3  | 15.2  | 32.2  | 28.9  |
| W-RR    | 46.5  | 55.8  | 28.6  | 21.7  | 21.3  | 50.6  | 46.6  | 28.9  | 14.9  | 38.1  | 0.7   | 27.3  | 42.5  | 53.0  | 17.4  | 22.8  | 30.4  | 16.4  | 16.7  | 43.5  | 31.2  |
| W-UG    | 54.4  | 49.6  | 31.5  | 24.8  | 27.0  | 42.3  | 62.9  | 6.6  | 21.2  | 34.6  | 0.3   | 18.2  | 35.4  | 51.3  | 33.9  | 15.0  | 8.3   | 33.9  | 2.6   | 49.0  | 30.1  |
| RR-UG   | 55.2  | 57.8  | 24.8  | 17.1  | 11.5  | 29.9  | 39.3  | 16.9  | 9.9   | 35.1  | 4.7   | 30.1  | 37.5  | 53.1  | 18.1  | 9.5   | 12.4  | 18.2  | 2.1   | 21.1  | 25.2  |
| RG-UG   | 49.8  | 56.9  | 20.9  | 15.6  | 10.8  | 25.6  | 42.1  | 14.7  | 4.1   | 32.4  | 9.3   | 20.4  | 28.0  | 51.2  | 14.7  | 10.3  | 12.6  | 14.2  | 9.5   | 28.0  | 23.6  |
| RG-RR   | 46.5  | 55.8  | 28.6  | 21.7  | 21.3  | 50.6  | 46.6  | 28.9  | 14.9  | 38.1  | 0.7   | 27.3  | 42.5  | 53.0  | 17.4  | 22.8  | 30.4  | 16.4  | 16.7  | 43.5  | 31.2  |

| IMGNET  |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |    mAP |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|       |
| RR-RR   | 34.3  | 34.6  | 19.9  | 17.1  | 10.8  | 30.0  | 33.0  | 18.4  | 9.7   | 13.7  | 1.4   | 17.6  | 17.7  | 34.7  | 13.9  | 11.8  | 15.2  | 12.7  | 6.3   | 26.0  | 18.9  |
| W-RR    | 35.9  | 23.3  | 16.9  | 15.0  | 11.8  | 24.9  | 35.2  | 20.9  | 11.2  | 15.5  | 0.1   | 15.9  | 15.6  | 28.7  | 13.4  | 8.9   | 3.7   | 10.3  | 0.6   | 28.8  | 16.8  |
| W-UG    | 38.6  | 32.5  | 18.7  | 14.1  | 9.7   | 21.2  | 36.0  | 9.9   | 11.3  | 13.6  | 0.9   | 15.7  | 15.5  | 32.3  | 15.9  | 9.9   | 9.7   | 19.9  | 0.1   | 17.4  | 17.1  |
| RR-UG   | 36.4  | 36.3  | 9.5   | 9.6   | 9.4   | 5.8   | 24.9  | 0.4   | 1.2   | 12.8  | 4.7   | 14.4  | 9.2   | 28.8  | 11.7  | 9.6   | 0.7   | 4.9   | 0.1   | 12.2  | 11.6  |
| RG-UG   | 32.7  | 34.5  | 20.2  | 14.6  | 9.4   | 7.5   | 30.1  | 12.1  | 2.3   | 14.6  | 9.3   | 15.2  | 11.2  | 30.2  | 12.3  | 11.4  | 2.2   | 9.9   | 0.5   | 13.1  | 14.7  |
| RG-RR   | 26.4  | 38.2  | 21.0  | 15.4  | 12.1  | 26.7  | 34.5  | 18.0  | 8.8   | 16.4  | 0.4   | 17.0  | 20.9  | 32.1  | 11.0  | 14.7  | 18.4  | 14.8  | 6.7   | 32.0  | 19.3  |
Learning Object Detector from 3D Models (4/5)

- Adding side view to front view gives a boost.
- Less invariance.

<table>
<thead>
<tr>
<th>IMAGNET</th>
<th>aero</th>
<th>bike</th>
<th>bird</th>
<th>boat</th>
<th>botl</th>
<th>bus</th>
<th>car</th>
<th>cat</th>
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<td>0.9</td>
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<td>19.3</td>
<td>37.5</td>
<td>30.3</td>
</tr>
</tbody>
</table>
When the number of real training images is limited, 3D models performs better than traditional RCNN over limited training data.
Augmented Reality for Data Generation (1/3) – Motivations

- Creating realistic 3D content is challenging and labor-intensive.
- Real-world images at large scale is easy and directly provides real background appearances without complex 3D models
- **Augmented imagery** generalizes better than **synthetic 3D data** or **limited real data**
Augmented Reality for Data Generation (2/3) – Augmentation Pipeline

- Given a set of 3D car models, locations (manual or automatic) and environment maps
- Rendering high quality cars and overlay them on top of real images.
- The final post-processing step ensures better visual matching between the rendered and real parts of the resulting image.

Alhaija et al., Augmented Reality Meets Deep Learning for Car Instance Segmentation in Urban Scenes. BMVC 2017
Augmented Reality for Data Generation (3/3) – Impacts Measured by Instance (Car) Segmentation

- More data – real or augmented – are both helpful

- Augmented foreground cars with real backgrounds are effective
Face Recognition (Verification or Identification) by Varying (Multi-Tasking) Loss and Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#Images</th>
<th>#Persons</th>
<th>#Images per person</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASIA</td>
<td>0.49M</td>
<td>10K</td>
<td>50</td>
</tr>
<tr>
<td>VGGFace</td>
<td>2M</td>
<td>2K</td>
<td>1000</td>
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<tr>
<td>Megaface2</td>
<td>4.8M</td>
<td>672K</td>
<td>7</td>
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<tr>
<td>MS-celeb</td>
<td>10M</td>
<td>100K</td>
<td>100</td>
</tr>
<tr>
<td>UMDFace</td>
<td>0.37M</td>
<td>8.5K</td>
<td>40</td>
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</tbody>
</table>
Industry Example – Augmented Glasses for Face Recognition (1/2) by Video Surveillance SBU, LiteOn

- Problem – Each pair is the same person but predicted to different people (red pairs) by the deep methods because of thick glasses
- Why? Few faces with glasses in most face datasets but common in Asian
Industry Example – Augmented Glasses for Face Recognition (2/2) by Video Surveillance SBU, LiteOn

- Glass invariance augmentation by overlapping variant glass models

- Impacts on proprietary benchmarks include 21,570 face (glass) pairs

<table>
<thead>
<tr>
<th></th>
<th>w/o glasses aug.</th>
<th>w/ glasses aug.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>99.207%</td>
<td>99.420%</td>
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<tr>
<td>Error case on glasses</td>
<td>109</td>
<td>40</td>
</tr>
</tbody>
</table>
(Real-Time) Style Transfer by Perceptual Losses

CycleGAN for Synthesizing “Realistic” Training Data

- Zhu et al., Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks ICCV 2017
- Zhang et al., Translating and Segmenting Multimodal Medical Volumes with Cycle- and Shape-Consistency Generative Adversarial Network. CVPR 2018
CycleGAN for Synthesizing “Realistic” Training Data

- Purposes for synthesized medical images
  - as an intermedium in cross-modality image registration or learning
  - as supplementary training samples to boost the generalization capability

- Our modified CybleGAN for multimodal recognition for utilizing MRI and CT (here CT $\rightarrow$ MRI) in Nasopharyngeal Carcinoma (NPC)

recognized in GTC Taiwan 2018
How to Get Quality Training Data in an Effective and Efficient Way? – Four Strategies

- Data crawling
- Transformation
- Weakly (semi-) supervised
- Synthesizing

Winston Hsu. Investigating Data Augmentation Strategies for Advancing Deep Learning Training. GTC 2018
Take Home Messages
Take Home Messages

- Data are vital for learning paradigms but very costly
- Collecting more training data from public datasets
  - Used for multi-task learning or pre-training
- Augment data with
  - Social media
  - Synthesized data: transformed data, 3D, AR, GAN,
  - Work with the noisy data
  - Weakly supervised methods for minimizing human costs
- Data augmentation is vital for industry applications and will emerge as an important technical component
- Privacy! Privacy! Privacy!
Facebook, LinkedIn: “Winston Hsu”
Advancing Future IC Functions with MediaTek (聯發科)

- MediaTek: Tier 1 IC company
- Industrial-academic (mega) project
  - 5G and heterogeneous computing
  - MOST co-sponsored
  - 3-year
  - Few dozens of faculties involved
- Helping prototype the **compact** neural networks model
- Product shipping now
Visual Recognition for Consumer Photo Management with Synology (群暉)

- World #1 provider in network attached storage (NAS) ; a software company
- Photos and videos are major customer data
- Very STRONG users’ needs in
  - Object/scene recognition
  - Face recognition
- Ongoing Industrial-academic collaboration
Bringing AI Capability for Hardware-Oriented System Company LiteOn (光寶)

- World leading companies in
  - IoT (Internet of Things),
  - LED lighting,
  - automotive,
  - biotech, and
  - industrial automation

- "Was" hardware-oriented

- Helping grow the AI team and deliver world-competitive face recognition system
  - Edge-side
  - Server-side
AI-Enabled Video Editing with CyberLink (訊連)

- **CyberLink**: world leading image/video software company
- Helping found and grow the AI team
  - Image/video recognition
  - Style editing for video (recently released)
Google Street View Time Machine

- The same locations are depicted at different times and seasons
  - Invariance to lighting, viewpoint, partial occlusions
  - Confusing features: cars, people, vegetation, clouds

Arandjelović et al., NetVLAD: CNN architecture for weakly supervised place recognition, CVPR 2016
Learning from Time Machine data

- Weakly supervised ranking loss

Potential positives

Definite negatives

Query

Closest positive

At least one positive image