Practical Methodology in Deep Learning

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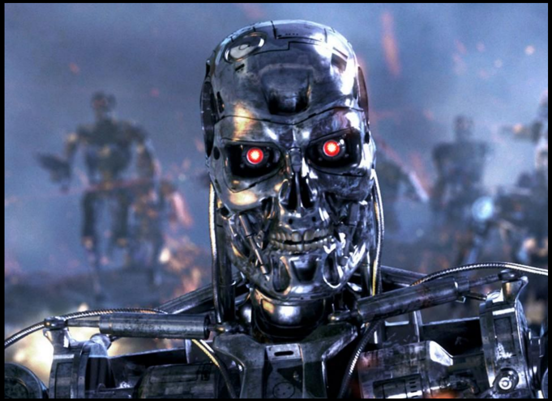
Deep Learning



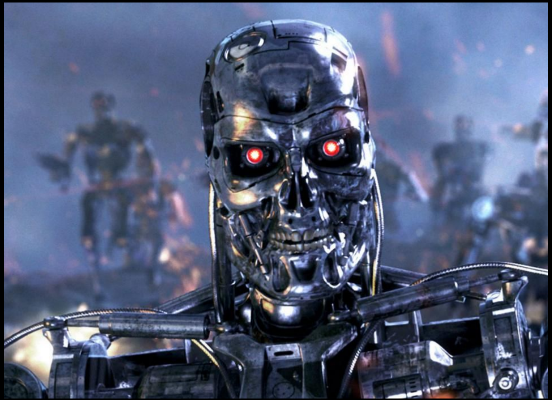
What society think I do

What my mom think I do

What I think I do

What I really do

Deep Learning



What society think I do

What my mom think I do

What I think I do

CNN调参 每层200 包SOTA

Caffe安装 20/次

Tensorflow安装 15/次

RNN调参 每层400 包SOTA

GAN调参

G网络800, D网络400

What I really do

Debugging Learning Algorithm

Regularized Supervised Learning

$$\min_\theta d(y, \hat{y}) + r(\hat{y})$$
$$\text{where } \hat{y} = f(X, \theta)$$

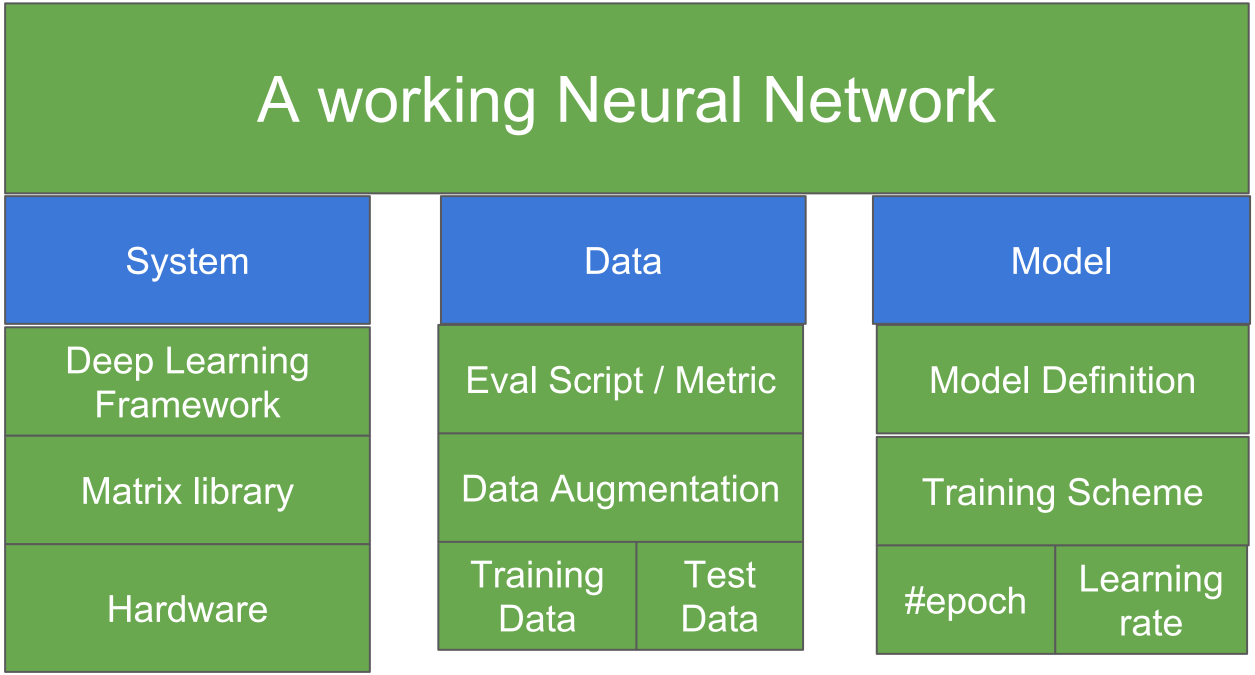
d measures distance between ground truth and prediction
Regularizer: ***r***

$$d(y, \hat{y}) = -\log p(y|\hat{y})$$
$$r(\hat{y}) = -\log p(\hat{y})$$
$$\Rightarrow d(y, \hat{y}) + r(\hat{y}) = -\log p(y)$$

d is conditional probability.
Regularizer ***r*** corresponds to prior.

$$C = d + r$$
$$\frac{\mathrm{d}\theta}{\mathrm{d}t} = -\frac{\partial C(\theta(t))}{\partial \theta} \Rightarrow \frac{\mathrm{d}C(\theta)}{\mathrm{d}t} = \frac{\partial C(\theta)}{\partial \theta}\frac{\mathrm{d}\theta}{\mathrm{d}t} = -\left(\frac{\partial C(\theta)}{\partial \theta}\right)^2 \leq 0$$

Behind a working Neural Network



$$\min_\theta d(y, \hat{y}) + r(\hat{y})$$
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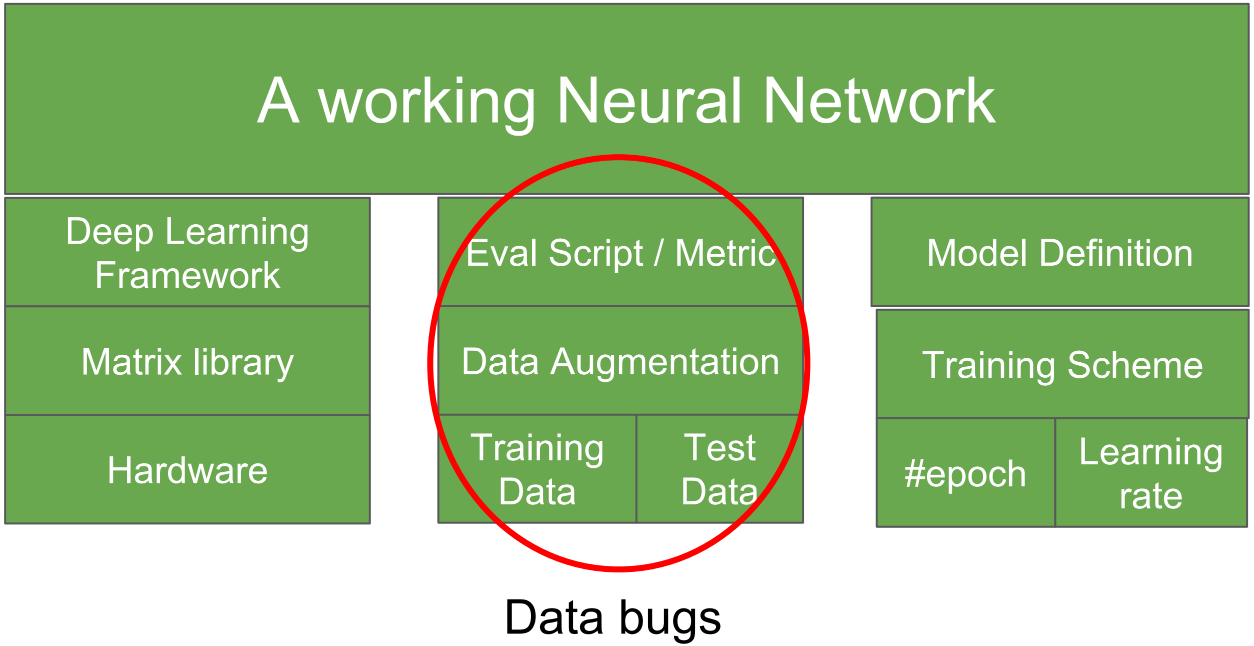
Behind a working Neural Network



$$\min_\theta d(y, \hat{y}) + r(\hat{y})$$
$$\text{where } \hat{y} = f(X, \theta)$$

Data bugs: improper input

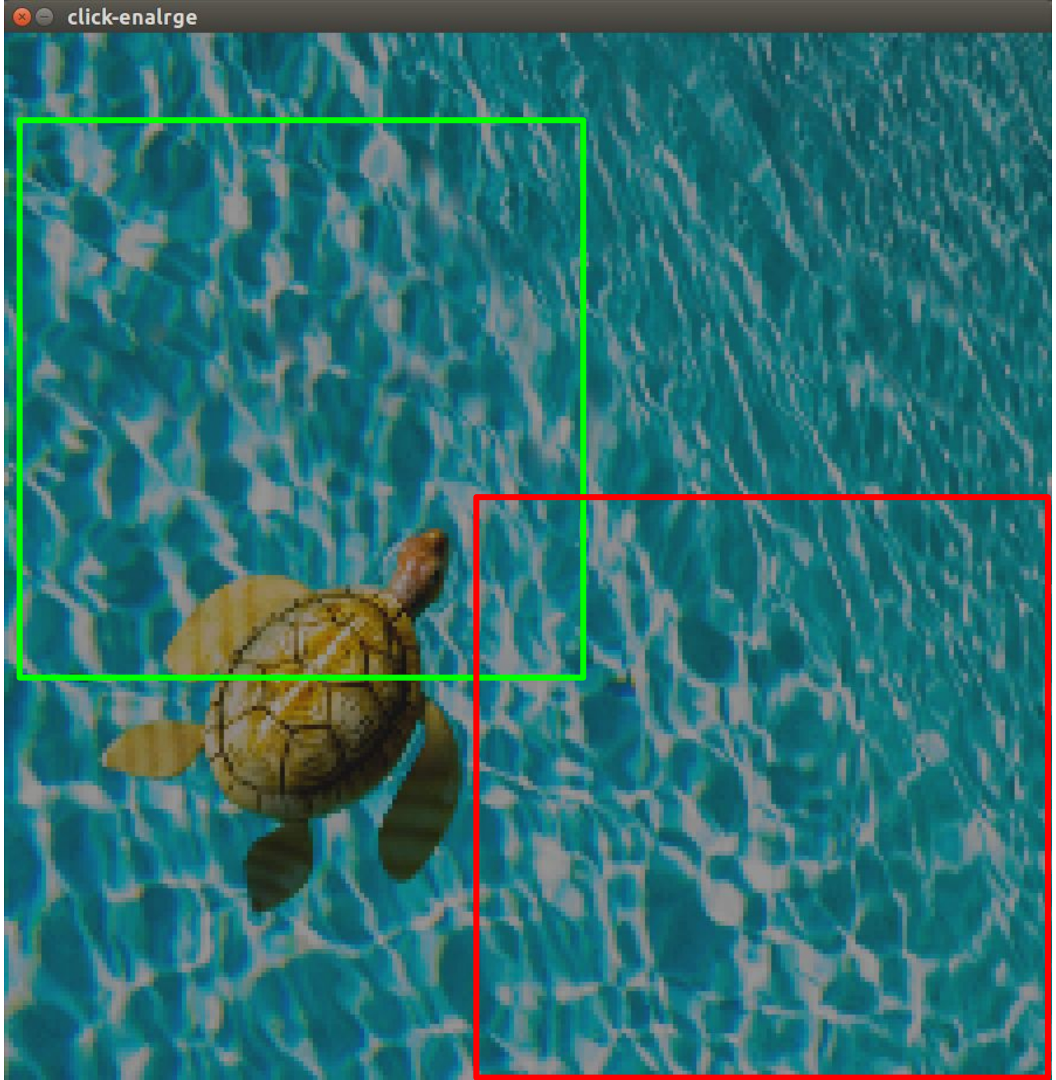
- A neural network is to some extent robust to such distortions
  - Hard to spot subtle error
  - Need visualization
    - Listing the top errors
    - View random samples

Bad Aspect Ratio

RGB or BGR?

Augmentation: random cropping

- Tradeoff between augmentation strength and augmented data quality
  - Too strong augmentation make data invalid
  - Too weak augmentation degrades generalization ability
- Rule-of-thumb
  - The bad augmentation percentage should not exceed prediction error rates.



Need label be also transformed when augmenting?

For heatmaps, should also apply geometric transform. But should there also be blurring?

Data bug: what the classifier really is

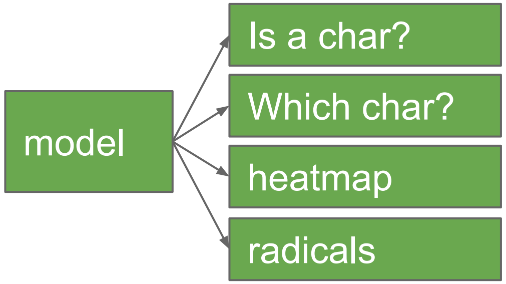
No

Tank classifier, or weather classifier?

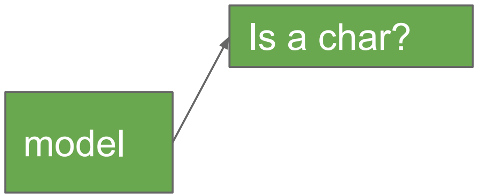
Yes

Data bug: what the classifier really is

- Solution: multi-task learning
  - Can use additional supervision signal for training, but can omit when inference.

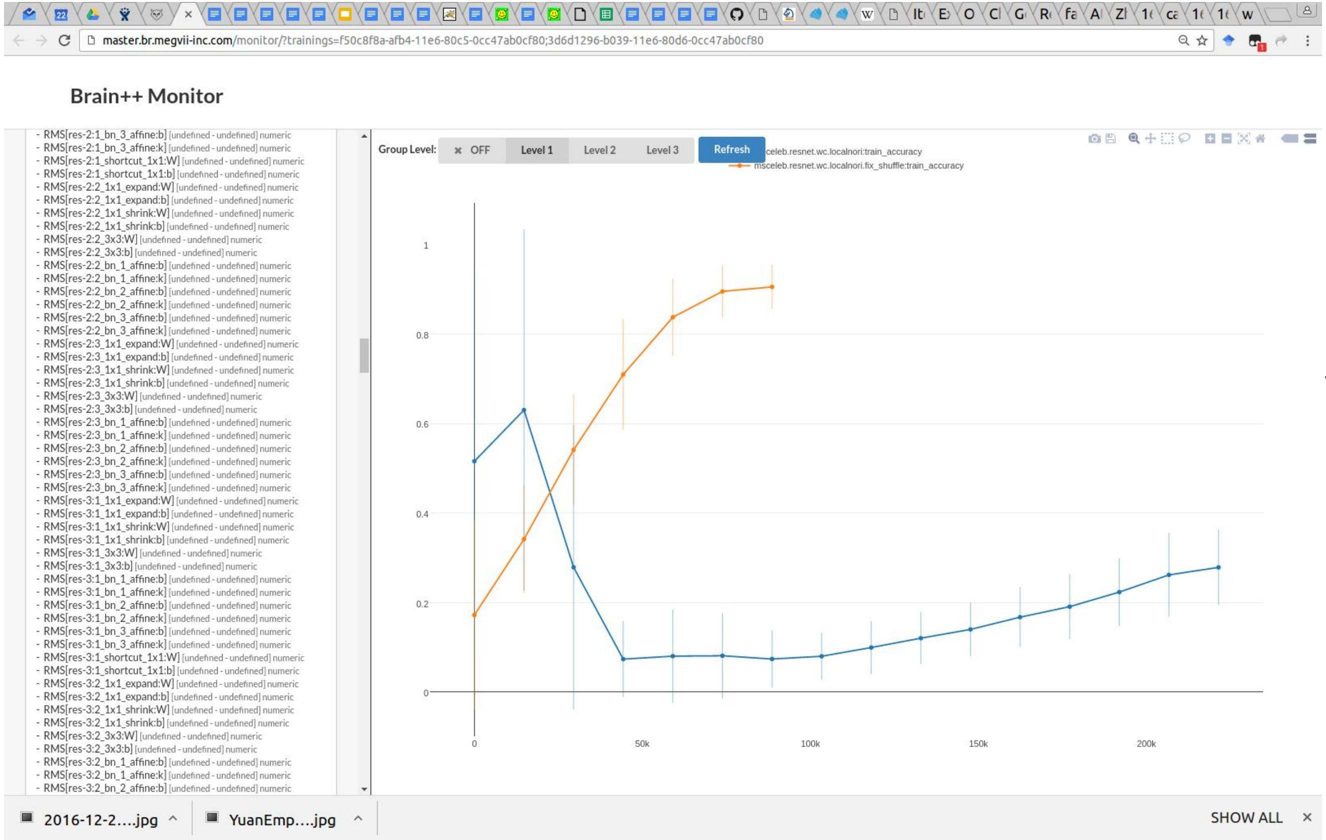


Train time



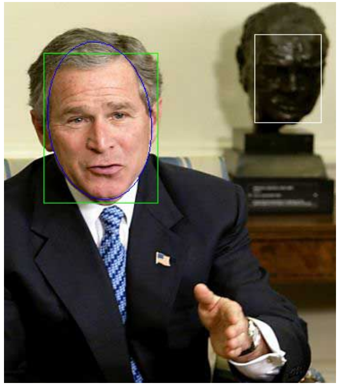
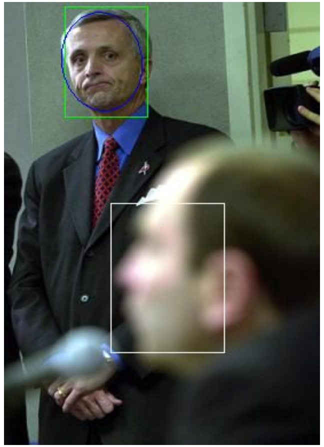
Inference time, no extra computation

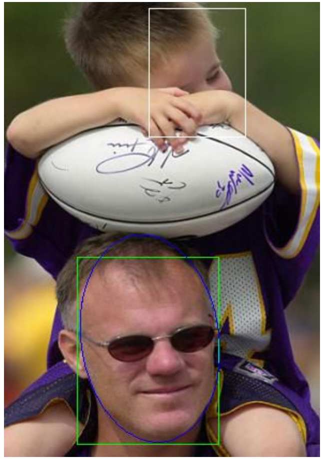
Data bug: sample with replacement is bad

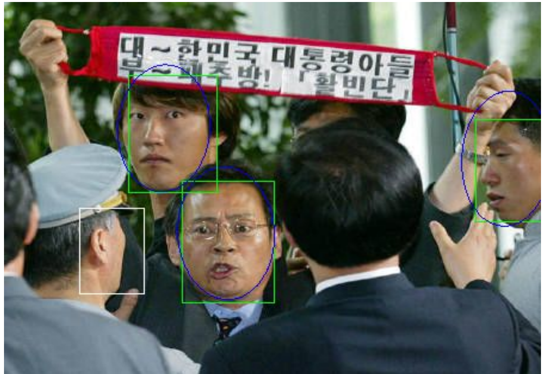


np.random.choice is with replacement by default.

Eval metric can be wrong



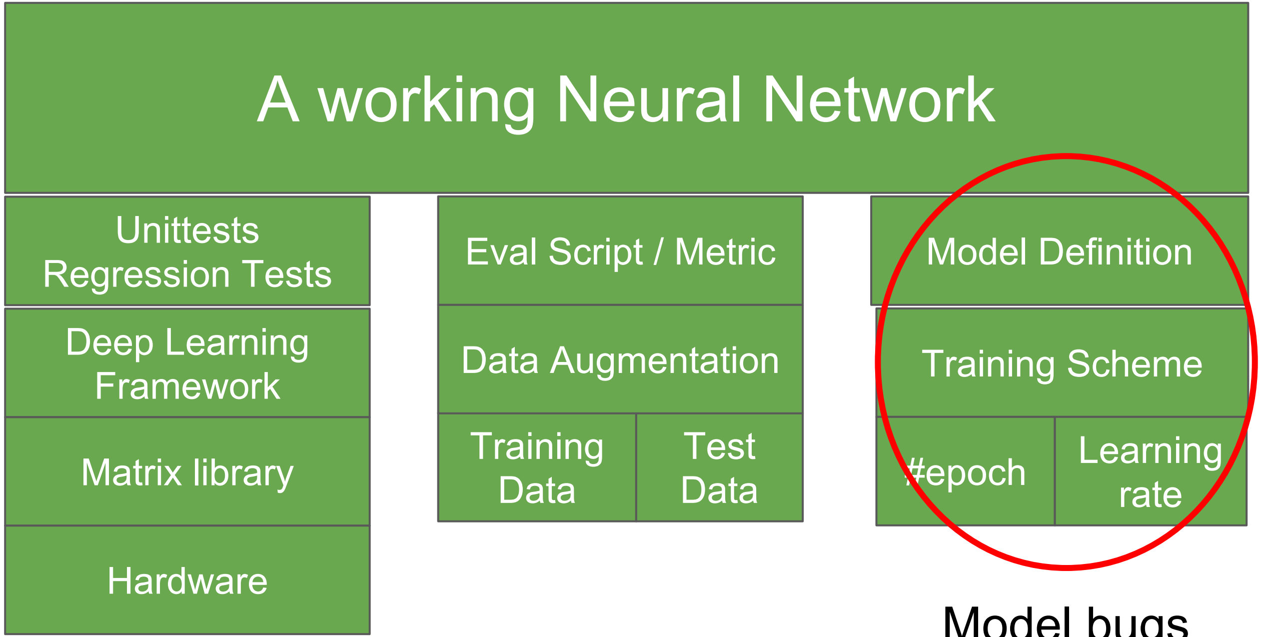



Check the misclassifications

Data checklist

- Training Data
  - Visualize the images and check the classes
    - Can a human learn the task?
    - De-duped and shuffled?
  - Visualizing the augmented images
    - Augmentation too strong?
    - Need label to also transform?
- Test Data
  - Drawn from the same distribution as Training data?
  - Is it really segregated from Train?
    - Simply different images may be insufficient.
      - For face recognition, need be images of different persons
  - Properly de-duped?

Behind a working Neural Network



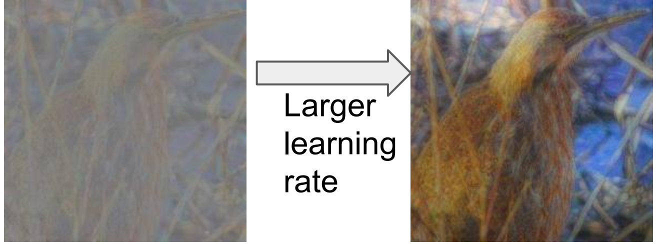
Model bugs

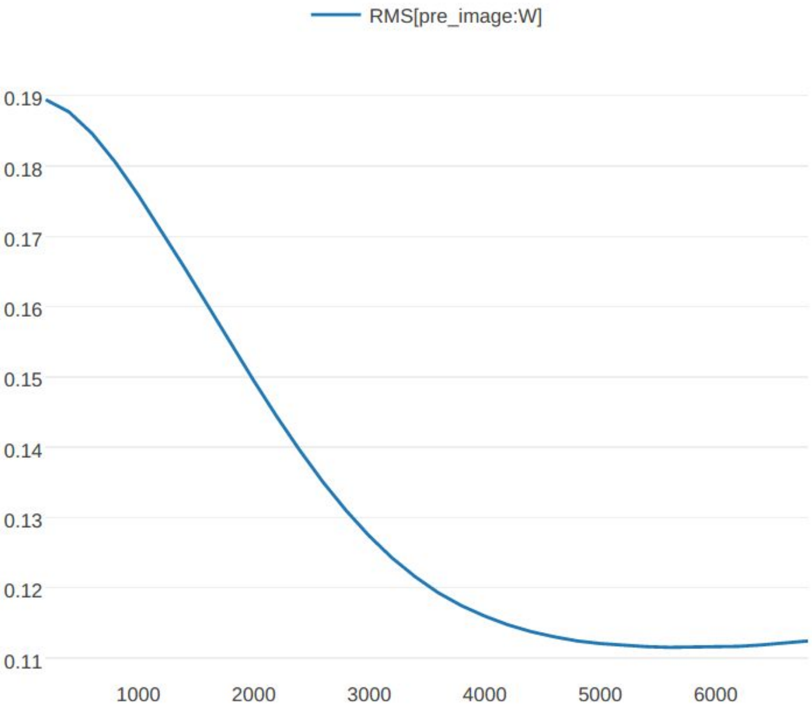
$$\min_\theta d(y, \hat{y}) + r(\hat{y})$$
$$\text{where } \hat{y} = f(X, \theta)$$

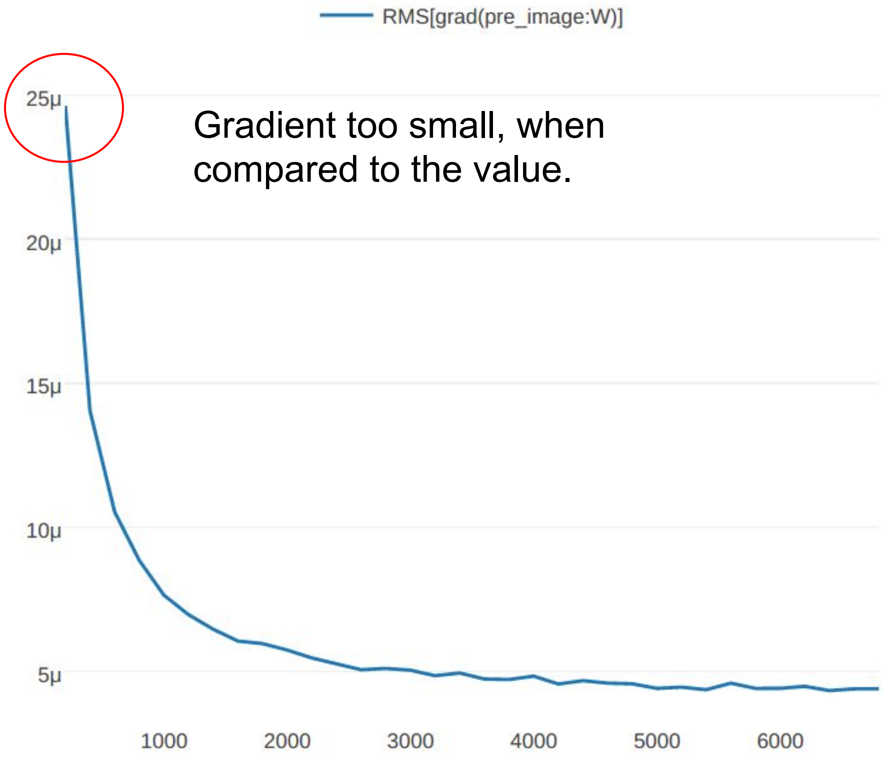
Model bug: weight value range

- Symptom
  - Binarized model converges slowly on MNIST
    - Reference implementation has validation error rate 3.53% after 3 epochs
    - Our implementation only gets 14% after 58 epochs
- Debug Process
  - Read the logs, find the training misclassify also as high as 15%.
    - The model is underfitting
  - A line of control experiments to test the differences between ours and reference
- Conclusion
  - Need to change the value range of quantized weights from {0, 1} to {-1, 1}
    - Gets 2.9% error rate after 10 epochs

Learning rate tweaking



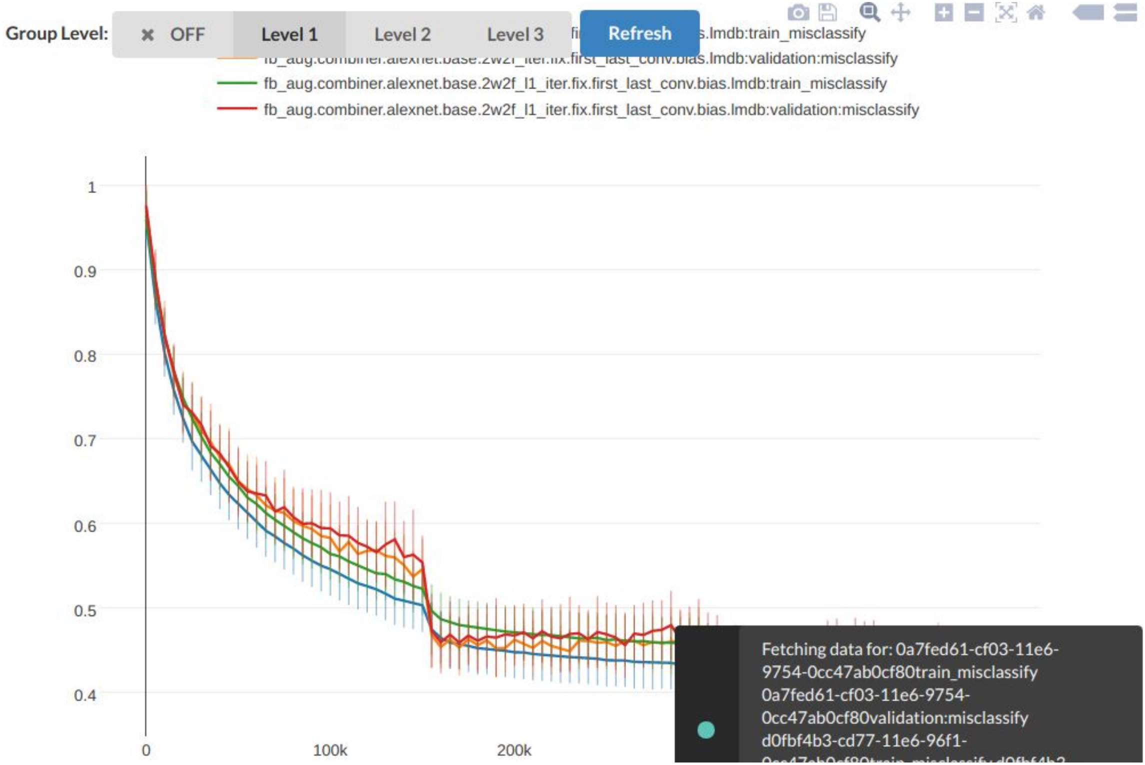




Gradient too small, when compared to the value.

Diagnostics for debugging learning algorithms

- Training error near zero?
- Loss normal?
- Parameter scale normal?
- Gradient scale normal?
- Activation scale normal?
- Validation error near zero?



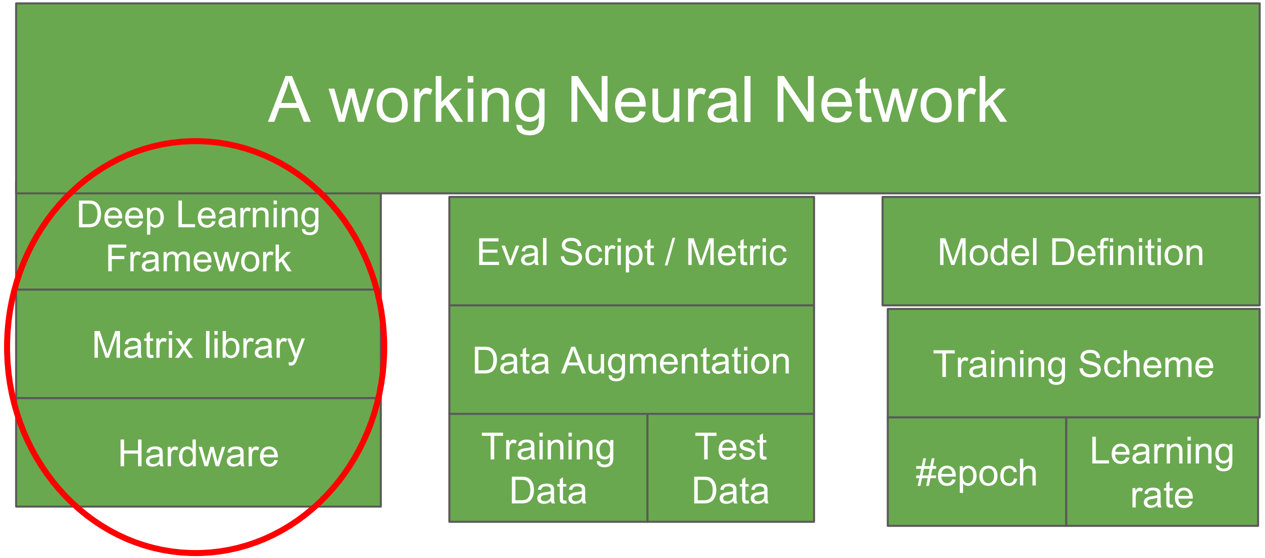
Error analysis

- Visualize the heatmaps

Document the trials and ensure reproducible

- Global Tree Naming
  - Offers ablative analysis
  - example: 中浙优8号
    - 中稻, 浙江产, 优, 8号
  - Specialized names: 隆平稻
    - reserved for exceptional good ones
    - serve to shorten name
- svhn.quarter_fc.no_epsilon.no_dupe.shuffled.lr_1e-3.adam
  - SVHN
  - quarter_fc: FC only has quarter #channel
  - no_epsilon + no_dupe: remove epsilon and dupes in labels before matching
  - Data are shuffled
  - Learning rate 1e-3
  - ADAM

Behind a working Neural Network



System bugs

$$\min_\theta d(y, \hat{y}) + r(\hat{y})$$
$$\text{where } \hat{y} = f(X, \theta)$$

System bugs

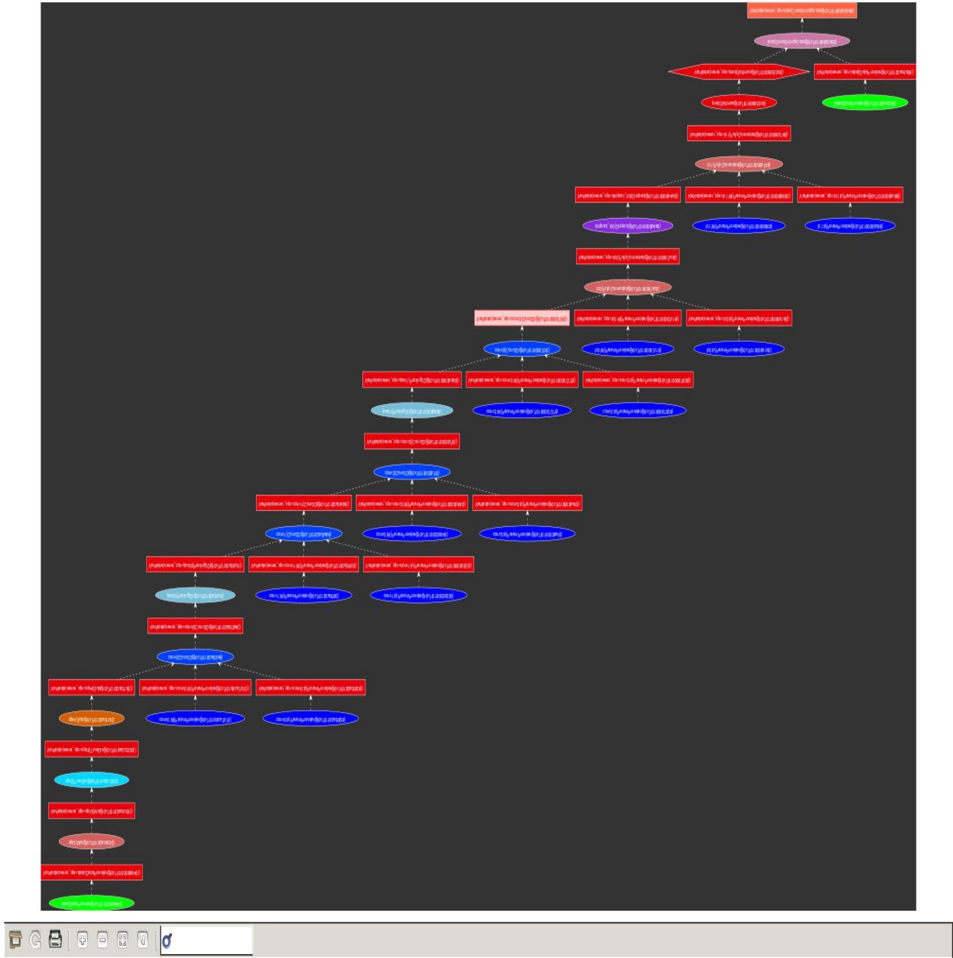
- Source
  - Problematic Optimizations for acceleration
    - Especially the branches for different architectures and input shapes.
  - Failing hardware
- Solution
  - Numeric unit tests, especially for gradients
  - Known-to-work NN, like MNIST/SVHN
  - Falling back to the most mature branch (X86) and turning off optimizations
  - A sense of *what-should-work*

Gaming graphic card producing wrong numbers

```
[r:0,c:1,out] 10 13:42:41[mgb] ERR caught exception in async worker `comp_node_dispatch:gpu0:0'; what(): var sanity check failed: var: {
id:2851180, layout:{1(1),1(1)}, Float32, owner:dimshuffle(fc2_bn_affine:k)[94764]:dup{Dimshuffle}, name:dimshuffle(fc2_bn_affine:k)[9476
4]:dup, slot:0, gpu0:0, s} (checksum: expect={checksum:0xbfd281e7, last_int:-1076723225, last_float:-1.64459} got={checksum:0xbfd26a62,
last_int:-1076729246, last_float:-1.64387}); receiver: MUL(dimshuffle[94764],POW[2645135])[2645139]:dup{Elemwise}(2854179); you can set
MGB_DEBUG_VAR_SANITY_CHECK_LOG=2851180 to get more details; pass=0
[r:0,c:1,out] bp:/opt/megdl/MegBrain/v5.14.2/_mgb.so{2e9158,28a241,319b41,319dd5}
```

System bug example: model output different

- Symptom
  - The prediction of model is different on CPU and GPU
- Debug process
  - Triage through the operator tree for the node that has different outputs
- Conclusion
  - The OpenCV resize has several optimizations that make it different from the definition



Speeding up Development

Development Flow

- Define the problem
  - Have a benchmark and a numeric metric
  - An intuitive end-to-end demo
- Iteratively refine pipeline (trial-and-error)
  - Analyze and understand the numbers and figures
    - Diagnostics for debugging learning algorithms.
    - Error analysis and ablative analysis.
  - Periodically optimize for the speed, make the method more practical
  - Document the trials (success and failures) and ensure reproducible

Have a benchmark and a numeric metric

- OCR
  - Text positions and content
    - Deal with duplications
    - Single char, or word?
    - Which blur texts to ignore?

Evolution of a pipeline

- Get a working pipeline first, before optimizing components.
- Pipeline should have less #hyper-parameters.

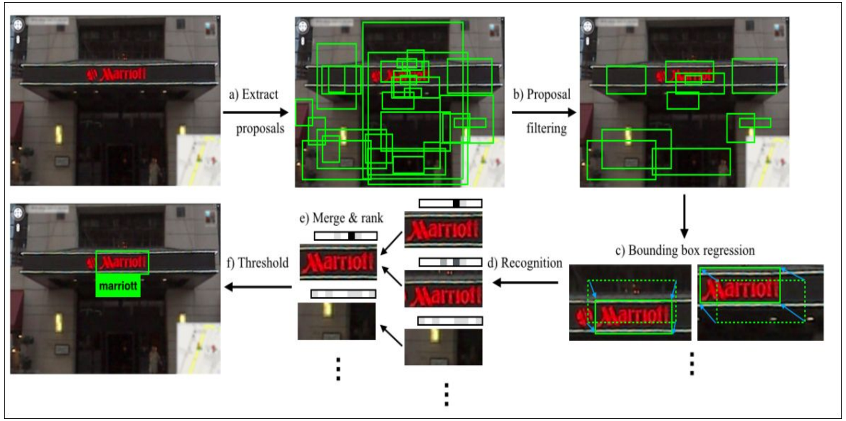
An intuitive end-to-end demo

https://www.youtube.com/watch?v=o5asMTdhmvA

Case study: OCR pipeline

- Merge these
  - Proposal
  - Filtering
  - Bounding box regression

Reading Text in the Wild with Convolutional Neural Networks, 2014



EAST: An Efficient and Accurate Scene Text Detector, 2017

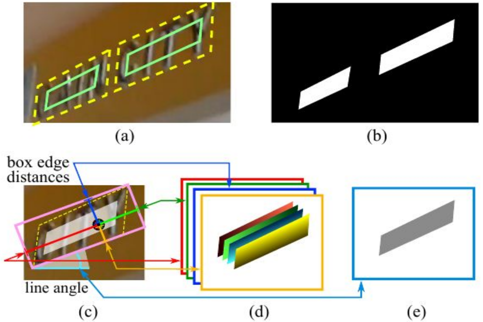
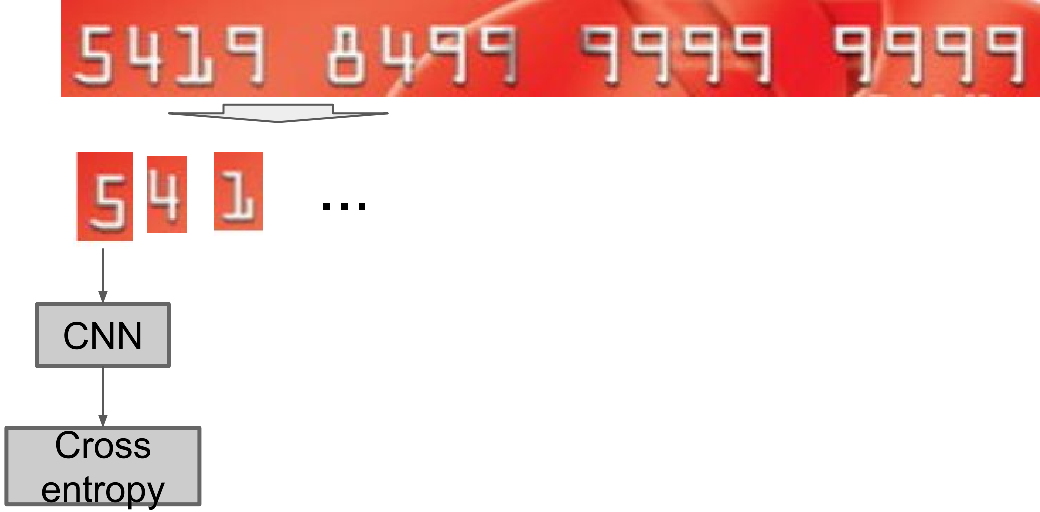
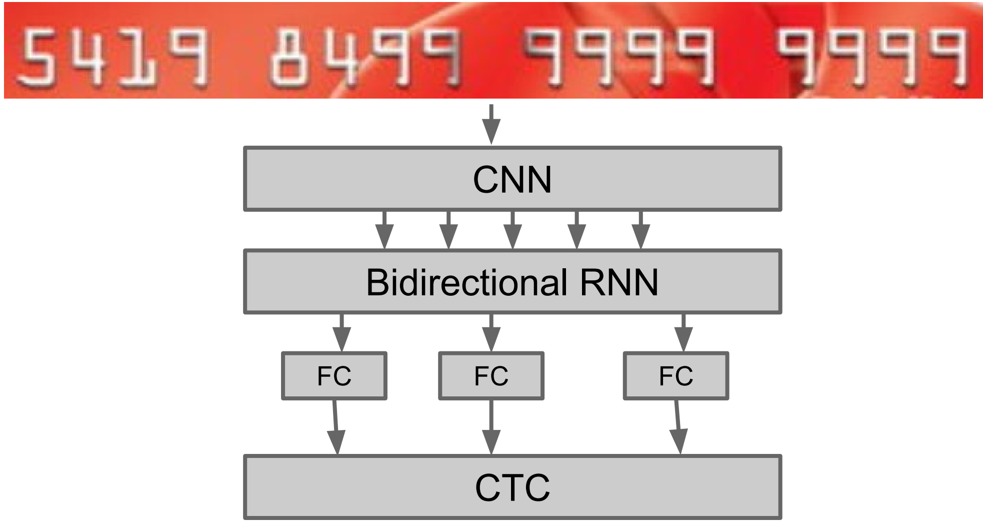


Figure 4. Label generation process: (a) Text quadrangle (yellow dashed) and the shrunk quadrangle (green solid); (b) Text score map; (c) RBOX geometry map generation; (d) 4 channels of distances of each pixel to the rectangle boundaries; (e) Text rotation angle.

Pipeline design

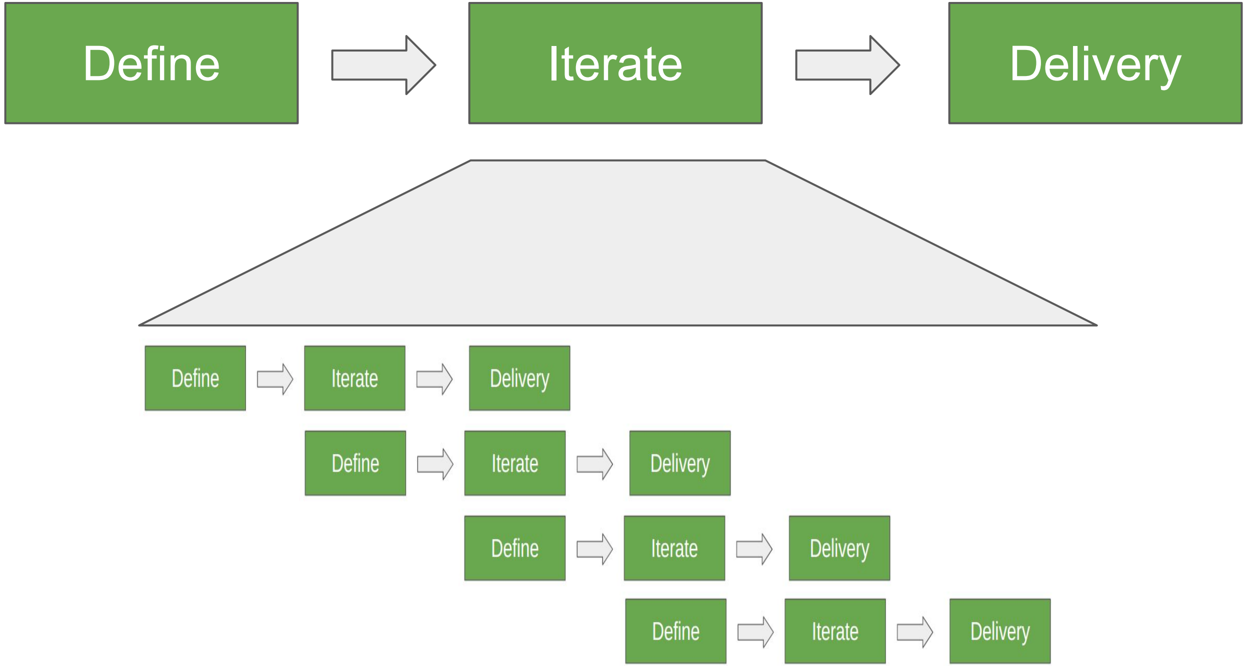
- Prefer end-to-end
  - If no proper metrics can be defined
- Prefer staged
  - If near-perfect accuracy
  - Allows breaking up work
    - Need define protocols





Periodically optimize for the speed

Pipeline of Trying Out Ideas



Periodically optimize for the speed

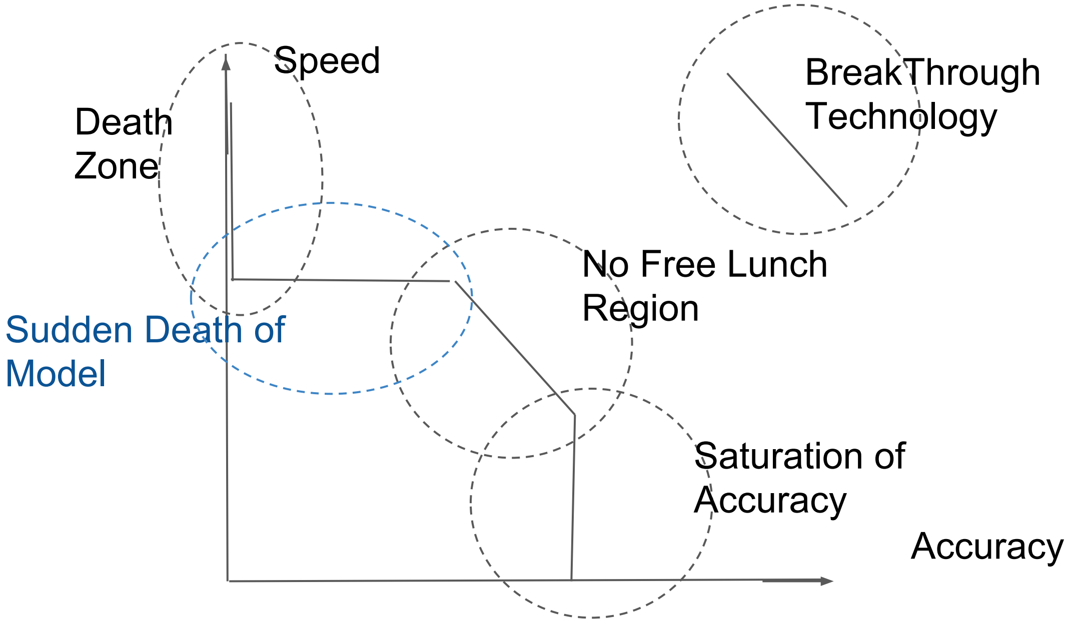
- Check list
  - Can we use less data?
  - Can we use smaller model?
  - Multi-card/multi-machine training?
  - Can augmentation speed be improved?
  - Can we parallelize the eval process?
  - **Can we automate the process?**

Rule-of-thumb for designing a model

- Best reuse an existing model, or part of it.
  - Models pre-trained on large datasets are powerful.
- ***log_2 input_image_size - 2*** down-samplings
  - Input image should be large enough for human to judge
- Determine #channel from computation budget
- If translation invariant, then use more convolutions.
- If too few parameters
  - Fully-connected or Locally-connected

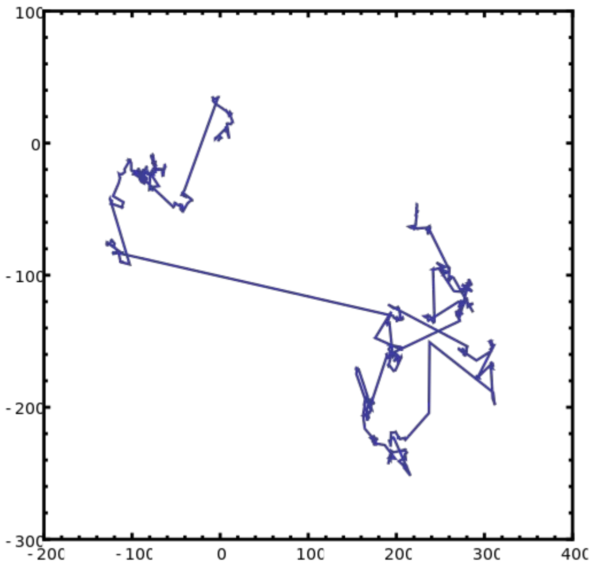
Tradeoff between Accuracy and Speed

- Breakthroughs improve both accuracy and speed
  - Factorized Convolution (GoogleNet)
  - Skip connection (ResNet)
  - Fully Convolutional Network
  - Better Loss Function
  - Batch Normalization



Searching for good model

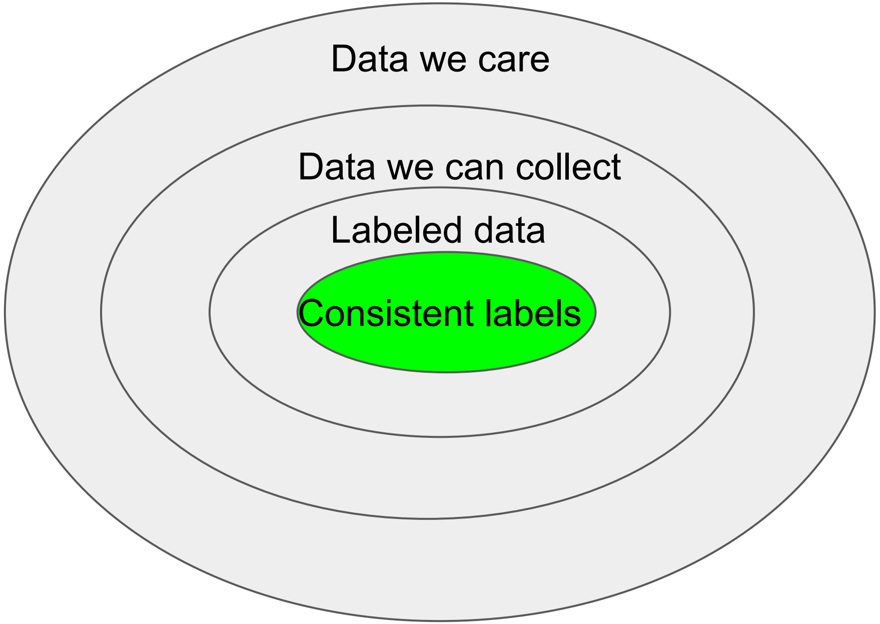
- Repeat: big-step, many baby-steps
  - Big steps helps you explore design space
    - Make wild changes and hope to get better
  - Baby step locally search for local optimum
    - Mostly in the form of control experiments where only one factor changes, to allow for later combination of factors
    - Should be densely logged



Lévy flight, one way animals find food.

Training with Synthesized Data

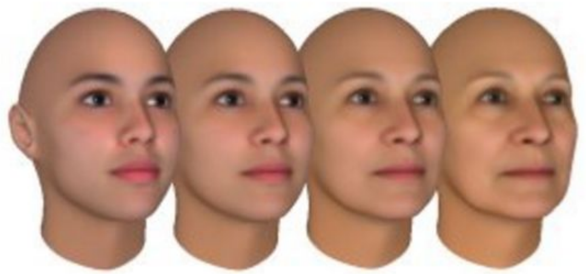
The scarcity of labeled data



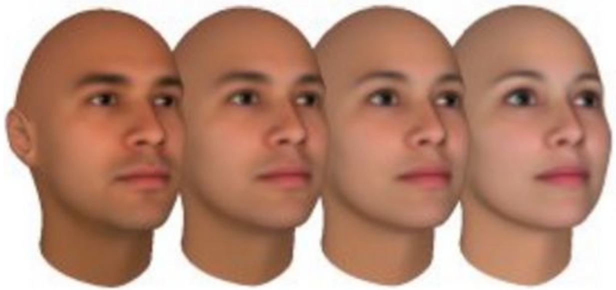
The scarcity of labeled data

- The data may be sensitive
  - Unlabeled ID card costs **70** yuan/image.
- Data like videos are hard to label
  - High frame rate x High resolution
- Even hard to define labels
  - Where's the border between face and non-face in this image? =>

Computer Graphics can handle 3D



Age Morphing

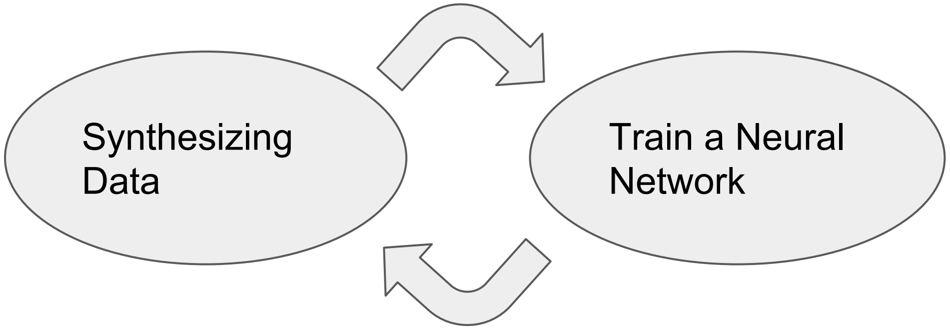


Gender Morphing

Skin Texture

Fast evolution without human labeling

Covers large variations.



Find some more corner cases.

Computer Graphics approach

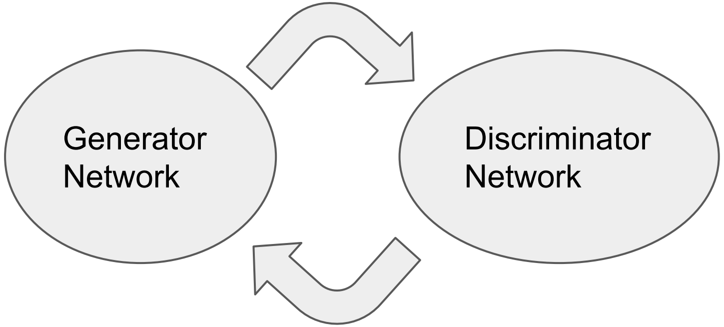
- Different standards of “real”-looking when used for NN training
- Synthetic data makes up ***all*** training data for ID cards.
  - after proper augmentation
- Engineering intensive

Neural Network Synthesizing

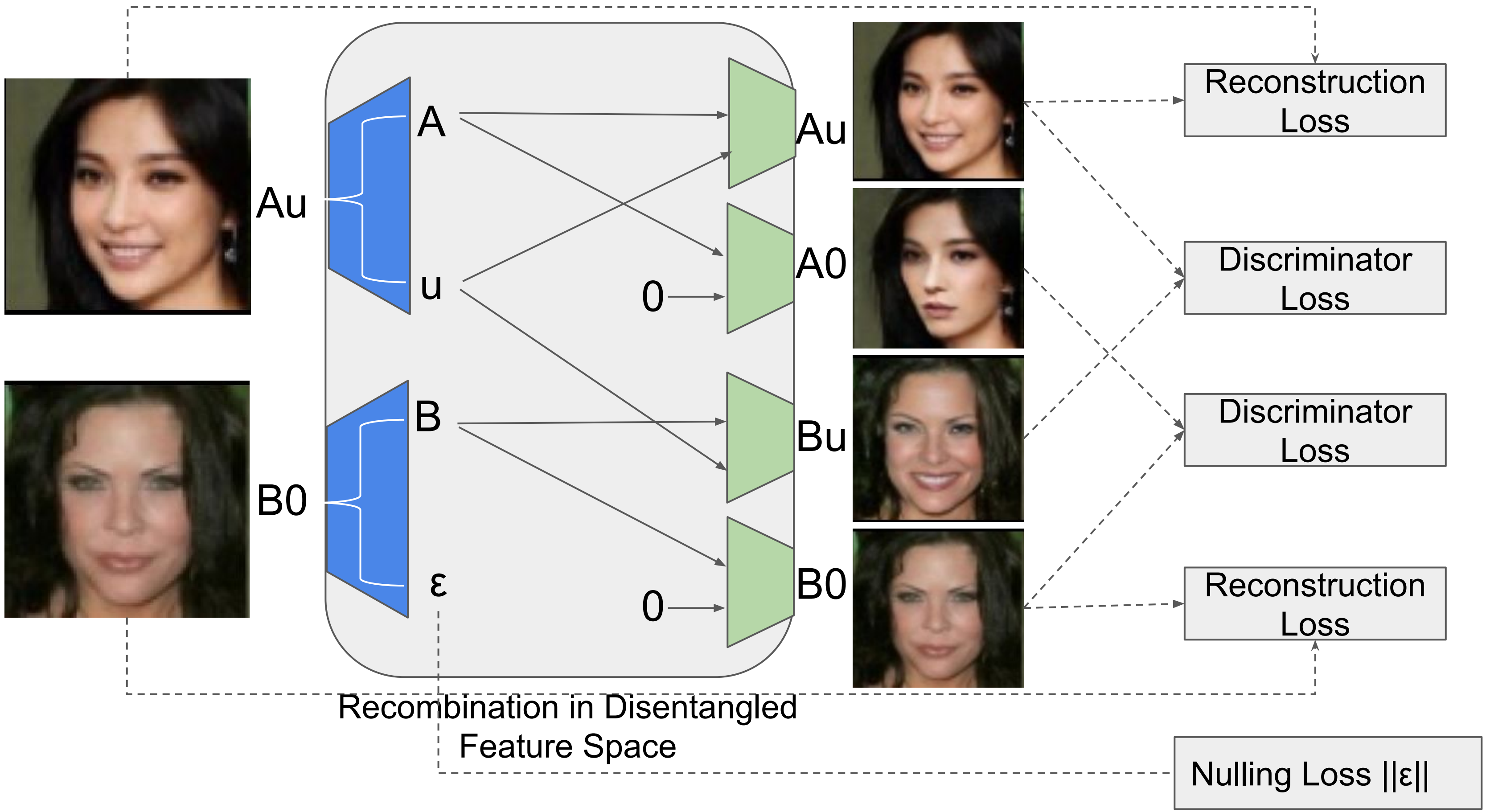
- "Inverse classifiers"
    - CNN: [Synthesizing chairs from attributes]
- Generative
    - RNN: [Creating non-existent Chinese char]

Generative Adversarial Network

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - \underbrace{D(G(\boldsymbol{z}))}_{\text{Take fake as true.}})]$$



GeneGAN



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Reconstruction Loss
Discriminator Loss
Discriminator Loss
Reconstruction Loss
Recombination in Disentangled Feature Space
Nulling Loss ||ε||

Summary

Solving Problems by Deep Learning

Upside	Downside
Can work on practical problems	Need deal with dirty details
Can context switch when model starts training	Long time to receive feedback
End-to-end pipeline boosts performance	Hard to peep into the all-in-one black box
Many techniques for improving quality	Hyperparameter search space large

References

- Chapter 11, Deep Learning
  http://www.deeplearningbook.org/contents/guidelines.html
- Advice for applying Machine Learning
  https://see.stanford.edu/materials/aimlcs229/ML-advice.pdf

Backup after this slide