

Siamese Network & AutoAug

Paper review

YU MO, 2022/07/11

The background of the slide features two jellyfish in a deep blue environment. The jellyfish have translucent, bell-shaped bodies with a pinkish-purple hue. Their internal structures, including the gastrovascular canals and the oral arms at the bottom, are visible. The jellyfish are positioned diagonally, with one slightly above and to the left of the other. The overall lighting is soft, creating a serene and ethereal atmosphere.

Siamese Network

Architecture & Loss Function

Siamese Network

Contributions

- Proposed the effective **Siamese Architecture** for classification/verification on large number of categories with only small train samples(Face recognition/Fingerprint recognition).
- Proposed a discriminative loss function which does not need to estimate the probability distribution of data.

Siamese Network Architecture

- **Shared** weights Convolutional Network. (Identical Network, one network)
- E_w is the defined similarity metrics called scalar energy function in the **energy-based models (EBM)**.

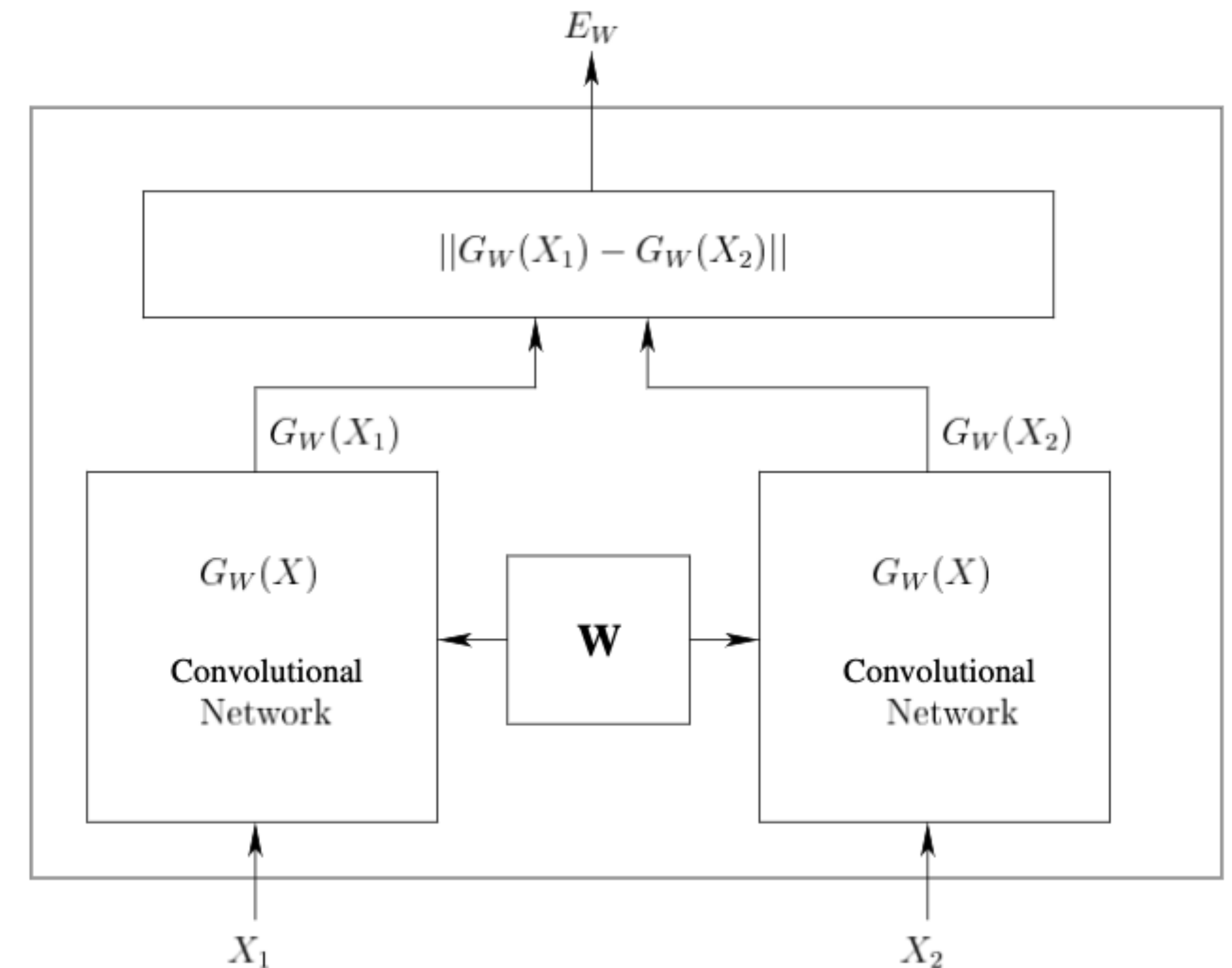


Figure 1. Siamese Architecture.

Siamese Network

Contrastive Loss Function in Training

- Energy function **E_W** should satisfy that energy of impostor pair should be large/increase and the energy of genuine pair should be small/decrease.
- Remaining part is to prove how to derive the Loss Function to meet the requirement.

$$E_W(X_1, X_2) = \|G_W(X_1) - G_W(X_2)\|$$

Energy Function



$$\mathcal{L}(W) = \sum \mathcal{L}(W, (Y, X_1, X_2)^i)$$
$$\mathcal{L}(W, (Y, X_1, X_2)^i) = (1 - Y_i) \mathcal{L}_G(E_W(X_1, X_2)^i) + Y_i \mathcal{L}_I(E_W(X_1, X_2)^i)$$

Loss Function design



$$\mathcal{L}(W, Y, X_1, X_2) = (1 - Y) \frac{2}{Q} (E_W)^2 + Y \cdot 2Q e^{-\frac{2.77}{Q} E_W}$$

Simplified Loss Function

Siamese Network

Results

- False accept(FA, 认伪(率))
- False reject(FR, 拒真(率))
- 3 datasets in total, trained in 2 datasets and verified on 3 datasets.

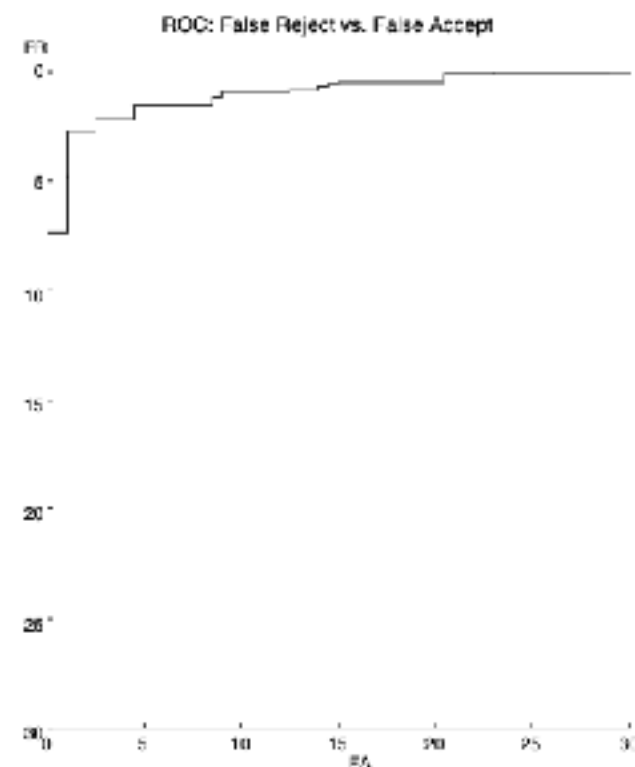


Figure 6. AT&T dataset: percent false reject vs. false accept.

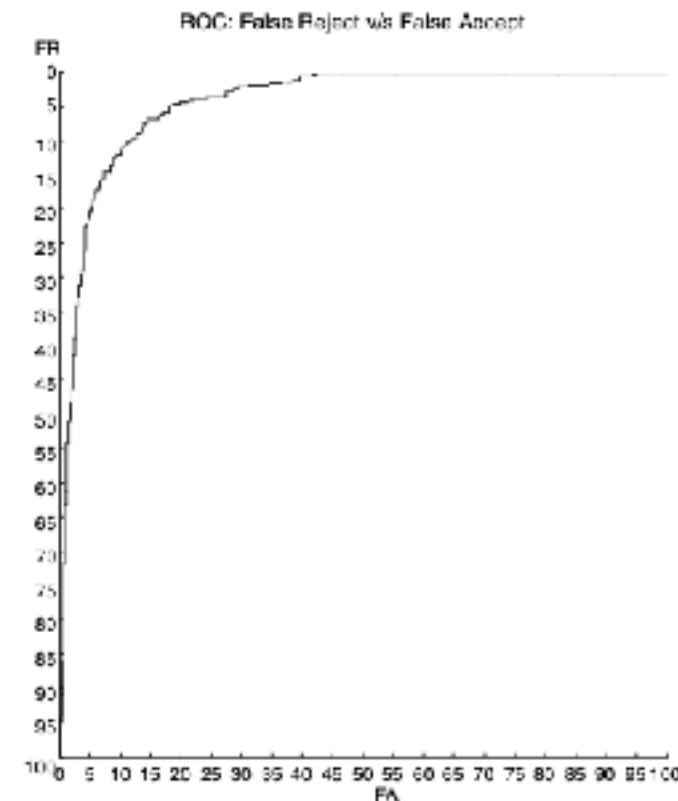


Figure 7. AR/Purdue dataset: percent false reject vs. false accept.

	AT&T		AR/Purdue	
	Val	Test	Val	Test
Number of Subjects	35	5	96	40
Images/Subject	10	10	26	26
Images/Model	—	5	—	13
No. Genuine Images	500	500	750	500
No. Impostor Images	500	4500	750	4500

	False Accept		
	10%	7.5%	5%
<i>AT&T (Test)</i>	0.00	1.00	1.00
<i>AT&T (Validation)</i>	0.00	0.00	0.25
<i>AR (Test)</i>	11	14.6	19
<i>AR (Validation)</i>	0.53	0.53	0.80

Table 1. Above: Details of the validation and test sets for the two datasets. Below: False reject percentage for different false accept percentages.

Siamese Network

Differences with Self-Supervised Learning

- Output is different. SSL is the trained network while SN is the label.
- SN is still need labels when training.
- The idea of loss function design is different.
- SSL maybe regarded as a special type of SN. Essentially, they are the same.

AutoAugment

Google Brain



AutoAugment: Learning Augmentation Strategies from Data

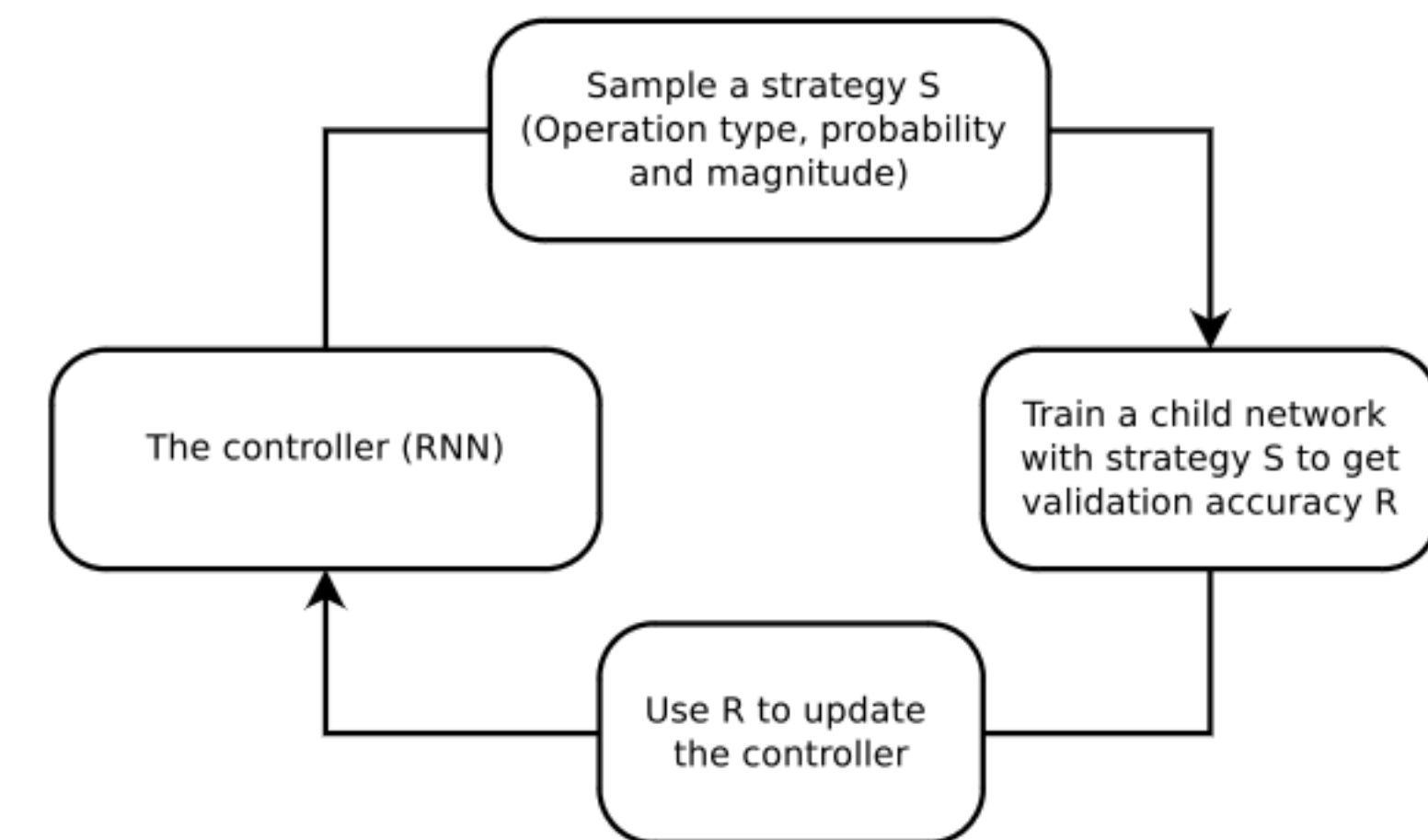
Contributions

- Automatically find the best augmentation policy (AutoAugment-direct) for any interested dataset.
- Find the transferable augmentation policy cross different datasets (AutoAugment-transfer)

AutoAugment

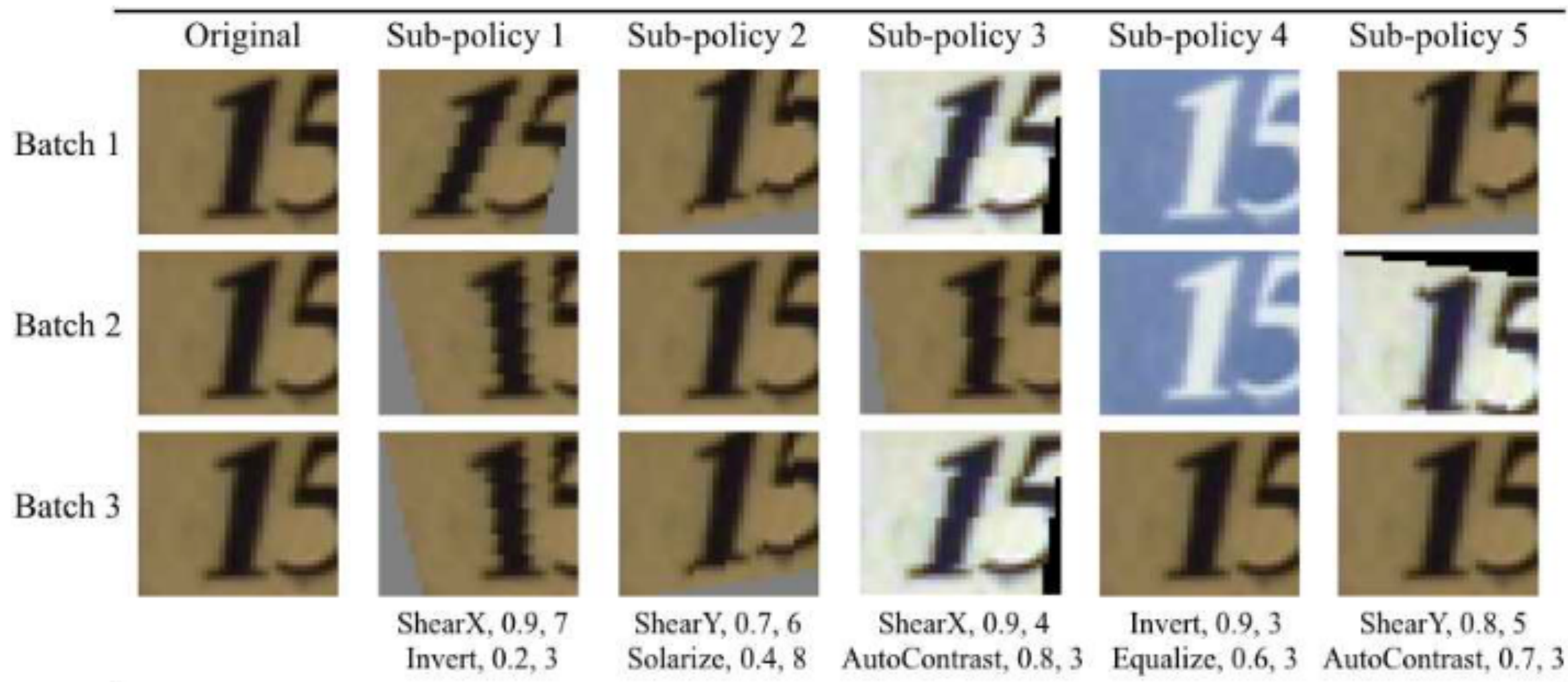
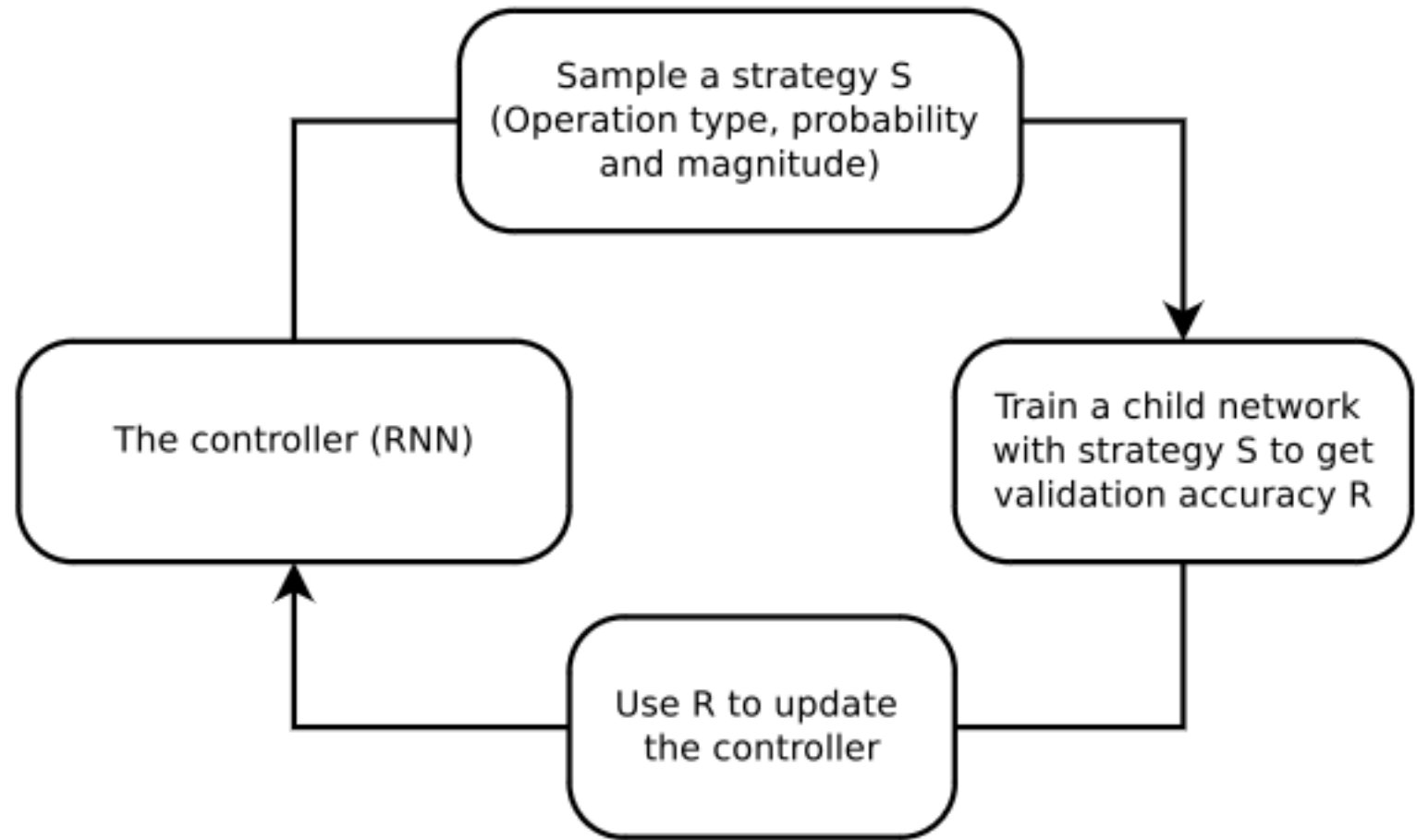
Problem definition

- Formulate the problem of finding the best augmentation policy as a discrete search problem.
- Two components: Search algorithm and Search space.
- Search algorithm: Reinforcement Learning
- Search space: 5 sub-policies or operations



AutoAugment

Workflow & Results



Dataset	Model	Baseline	Cutout [12]	AutoAugment
CIFAR-10	Wide-ResNet-28-10 [67]	3.9	3.1	2.6±0.1
	Shake-Shake (26 2x32d) [17]	3.6	3.0	2.5±0.1
	Shake-Shake (26 2x96d) [17]	2.9	2.6	2.0±0.1
	Shake-Shake (26 2x112d) [17]	2.8	2.6	1.9±0.1
	AmoebaNet-B (6,128) [48]	3.0	2.1	1.8±0.1
	PyramidNet+ShakeDrop [65]	2.7	2.3	1.5 ± 0.1
Reduced CIFAR-10	Wide-ResNet-28-10 [67]	18.8	16.5	14.1±0.3
	Shake-Shake (26 2x96d) [17]	17.1	13.4	10.0 ± 0.2
CIFAR-100	Wide-ResNet-28-10 [67]	18.8	18.4	17.1±0.3
	Shake-Shake (26 2x96d) [17]	17.1	16.0	14.3±0.2
	PyramidNet+ShakeDrop [65]	14.0	12.2	10.7 ± 0.2
SVHN	Wide-ResNet-28-10 [67]	1.5	1.3	1.1
	Shake-Shake (26 2x96d) [17]	1.4	1.2	1.0
Reduced SVHN	Wide-ResNet-28-10 [67]	13.2	32.5	8.2
	Shake-Shake (26 2x96d) [17]	12.3	24.2	5.9

Results