

#### Objectives

Investigate the use of Generative Adversarial Networks (GANs) for acoustic data generation given an initial small training set.

- Build a trainable generator for phone units and context windows.
- Develop the training pipeline to improve the pre-trained acoustic model's performance with augmented data.

### Background

Performance of a speech recogniser improves with increased training data size, **but** 

- collecting a large matched training dataset is difficult,
- manually transcribing speech data is expensive.

Generative Adversarial Networks are a method which can generate simulated data [1].

### **Methodology**

- Perform frame level speech data generation.
- Train separate GANs for each phonetic unit.
- Continue training the pre-trained acoustic model with augmented data (supervised training).



#### Figure 1: Architecture of whole system

#### **Generative Adversarial Networks**

- Discriminator is trained to perform classification between true data and fake data.
- Generator is trained to generate fake samples to fool the discriminator.

- Condition the model on phone states [3].
- Generate data on the speech feature level (FBANK).

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# **GANs for Speech Recognition Data Augmentation**

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GANs are a framework to estimate generative models via an adversarial-process:

- The configuration of our GAN:
- Use deep convolutional structure.
- Use spectral normalization technique [2].





## **Generated Fake Data**

model.







|  | Phone | Generated fake data |       |       | Test set data |       |       |
|--|-------|---------------------|-------|-------|---------------|-------|-------|
|  |       | %top1               | %top3 | %top5 | %top1         | %top3 | %top5 |
|  | aa[2] | 30.2                | 60.7  | 74.1  | 43.6          | 82.1  | 91.4  |
|  | aa[3] | 28.8                | 60.8  | 71.3  | 52.0          | 87.8  | 95.0  |
|  | t[2]  | 35.2                | 57.8  | 68.0  | 71.5          | 90.4  | 95.4  |
|  | th[2] | 45.1                | 69.6  | 78.2  | 42.8          | 69.6  | 78.2  |

# **Upcoming Work**

- Extend to triphone system.

#### References

- Adversarial Networks," pp. 1–9, 2014.

#### Evaluate the generated data based on the pre-trained acoustic



(c) Fidelity test for fake phone t[2]

Confidence Score Top10 (phone: aa[3])



(b) Fidelity test for fake phone aa[3]



(d) Fidelity test for fake phone th[2]

Table 1: Top1, Top3 and Top5 Classification Accuracy

# • Improve acoustic model performance with augmented data.

[1] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative

[2] T. Miyato, K. Toshiki, K. Masanori, and Y. Yuichi, "Spectral Normalization For Generative Adversarial Networks," 2018. [3] M. Mirza and S. Osindero, "Conditional Generative Adversarial Nets," pp. 1–7, 2014.