Shoe Design for the Future: Preliminary Steps

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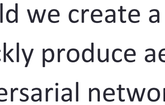
Introduction

- The fashion industry is now worth around $3 quadrillion
- A big subset of this field is shoe design
- The shoe industry continues to evolve, often combining influences from past and current trends
- Shoes that are 'hyped' can often be resold in the secondary market for many times their original retail price
- For instance, the Nike Yeezy Red October (below right), that retailed for $215, now sells for over $4,000



What comes next?

Problem Statement

Could we create a Shoe Generator for the future that is able to quickly produce aesthetic, shoe designs using a generative adversarial network?

More precisely, if we fed the Generator a vector of attributes signifying the type of shoe the user wanted and the type of qualities they desired, could the appropriate shoe be generated?

Dataset

- UT-Zap50K: dataset from the University of Texas for machine learning
- Contains 50,000 catalog images from zappos.com
- All footwear divided into 4 categories – shoes, boots, sandals and slippers
- Shoes divided into further 21 subcategories, such as oxfords, loafers, sandals etc.
- Dataset also contains 11,000 pair-wise comparisons between shoes. Attributes compared include comfortableness, pointiness, sportiness and openness.
- Preprocessed data to make images uniformly sized and omitted poorly curated categories

Approach

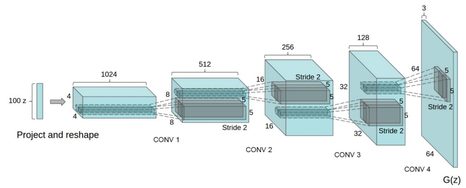
This project **will not** focus on building our dream Shoe Generator. Instead, we will be conducting 3 necessary preliminary steps:

1. Classification

Can a CNN classify these shoes into the appropriate functional categories? We used a modified GoogLeNet to create a functional type classifier.

2. Basic Shoe Generation

Next, we tried to produce a simple shoe generator by creating a DCGAN. It was trained on only the athletic shoes in our dataset.



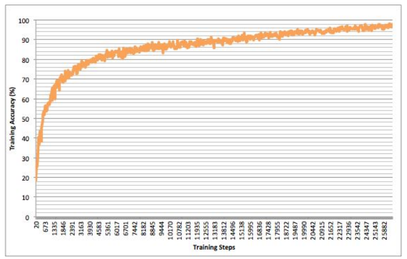
Generator Architecture

3. Attribute Scoring

Finally, we want to use a CNN to produce ordinal attribute metrics from the provided cardinal rankings. This will let us make a conditional Shoe GAN in the future. This CNN is currently still being trained.

Results: Classification

Classifier:

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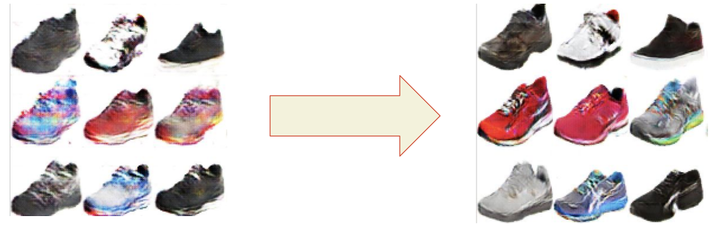
Training Step: 33385  | total loss: 0.06218 | time: 313.376s
| Momentum | epoch: 055 | loss: 0.06218 - acc: 0.9785 -- iter: 38842/38842
```

Results: Shoe Generation

Basic ShoeGan: Iteration 0 to Iteration 15 of training



Z ~ Uni(-1,1)

Z ~ Uni(-0.5,0.5)

Leaky Relu and SGD

Future Directions

We currently have trained a CNN to classify shoes into their 11 functional types, trained a GAN to create designs of athletic shoes, and are in the process of training a CNN to find instance-level attribute scores for each shoe in our dataset given attribute comparisons between shoes.

In the future, we hope to combine the components described above and improve the quality of our training set to create a powerful conditional GAN that takes a vector of attribute scores as inputs and generates shoe designs that reflect these attribute scores (e.g. the user can specify how pointy, comfy, sporty or open they want the shoe designs to be).

Works Cited

Kim, T. A tensorflow implementation of "Deep Convolutional Generative Adversarial Networks" https://github.com/carpedm20/DCGAN-tensorflow)
Yu, A. and K. Grauman. "Fine-Grained Visual Comparisons with Local Learning". In CVPR, 2014.
Radford, A., Metz, L., and Chintala, S. "Unsupervised representation learning with deep convolutional generative adversarial networks." *arXiv preprint arXiv:1511.06434* (2015).
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