# Simpsons CharacterRecognition Project

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## The Simpsons

Popular American animated sitcom

On air since 1989



#### Problem Statement

**Problem**: Large number of characters, sometimes we don't know who characters are while watching the show.

**Goal**: build deep learning models to detect and classify Simpsons characters.

#### Deployment:

Real-time character detection and classification. Viewers know who they are watching without pressing pause to check their phones.

#### Dataset

```
Public dataset

18,992 pictures for 18 characters

Divide into 3 sets of data

Training (60%)

Validation(20%)

Test (20%)
```

## Dataset Examples - Easy





## Dataset Examples - Medium





## Dataset Examples - Hard







#### Dataset - Challenge

Wrong character labels



Missing bounding box labels for images with multiple characters

Affect our ability to test model performance for part 2

detection



#### Data Cleaning & Augmentation

Convert images to pixels and normalized

Randomly rotate images (rotationrange=15)

Randomly zoom inside pictures (zoom\_range=0.2)

Randomly apply shearing transformations (shear\_range=0.2)

Randomly flip images horizontally

Randomly shift images horizontally/vertically (shift\_range=0.2)

#### VGG16/VGG19

	Softmax				
fc8	FC 1000				
fc7	FC 4096				
fc6	FC 4096				
	Pool				
conv5-3	3 × 3 conv, 512				
conv5-2	$3 \times 3$ conv, $512$				
conv5-1	3 × 3 conv, 512				
	Pool				
conv4-3	3 × 3 conv, 512				
conv4-2	3 × 3 conv, 512				
conv4-1	3 × 3 conv, 512				
	Pool				
conv3-2	3 × 3 conv, 256				
conv3-1	3 × 3 conv, 256				
	Pool				
conv2-2	3 × 3 conv, 128				
conv2-1	3 × 3 conv, 128				
	Pool				
conv1-2	3 × 3 conv, 64				
conv1-1	3 × 3 conv, 64				
	Input				

Softmax
FC 1000
FC 4096
FC 4096
Pool
3 × 3 conv, 512
Pool
3 × 3 conv, 512
Pool
3 × 3 conv, 256
3 × 3 conv, 256
Pool
3 × 3 conv, 128
3 × 3 conv, 128
Pool
3 × 3 conv, 64
3 × 3 conv, 64

#### VGG16

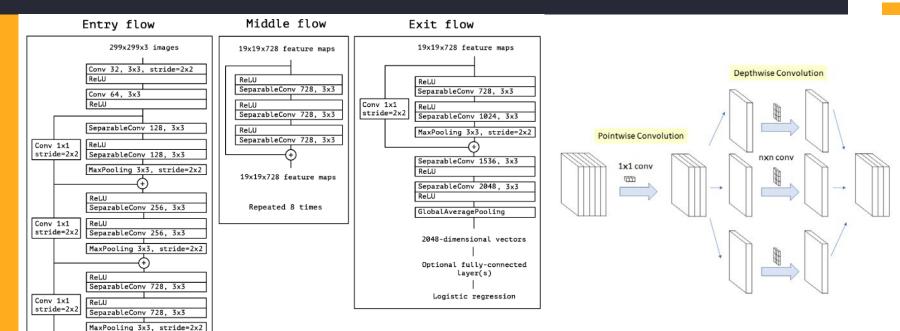
- Convolutional layers
- Pooling layer
- Flatten layer
- Dropout layer

#### VGG19

• Similar to VGG16, except it has four convolutional layers in the fourth and fifth block.

### Xception (Extreme version of Inception)

19x19x728 feature maps



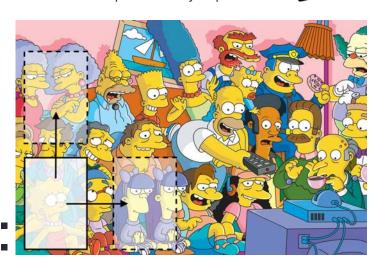
#### Object Detection: Faster R-CNN

Use sliding window and apply a CNN to many different Fixed Region Proposals?

crops of the image?

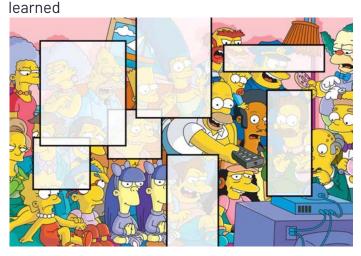
Inflexible Size

Too computationally expensive

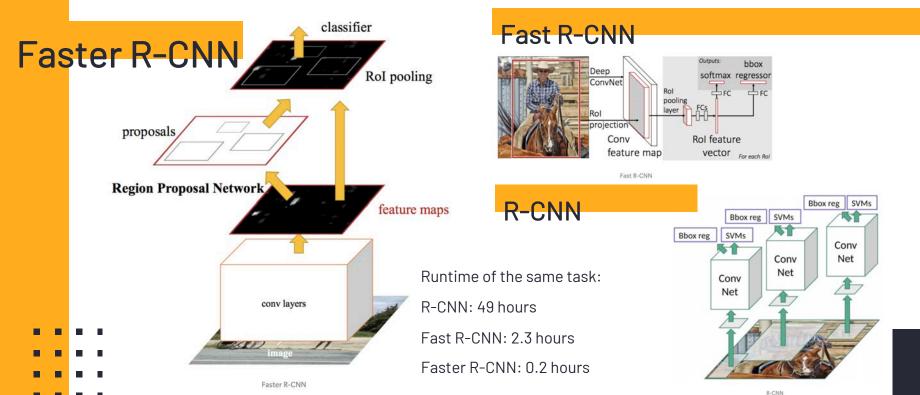


Select 2000 region proposals in a few seconds on CPU and apply a CNN to each one of them?

Better, but not enough! The region proposals should be



#### Object Detection: Faster R-CNN



#### Part I - Simpson Characters Classification

**Evaluation Metrics** 

Test Accuracy

Test Loss

Precision

Recall

#### **VGG 16**

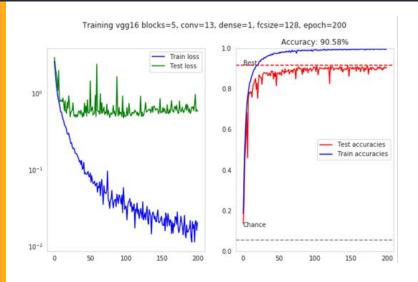


Image size (32,32)

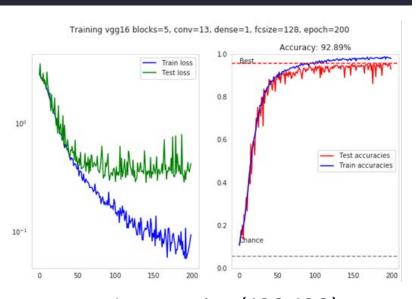


Image size (128,128)

#### **VGG 19**

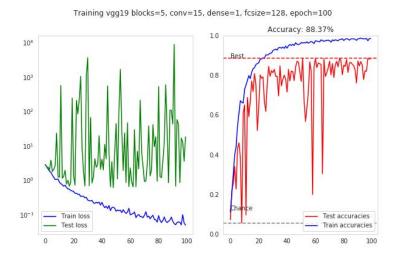


Image size (32,32)

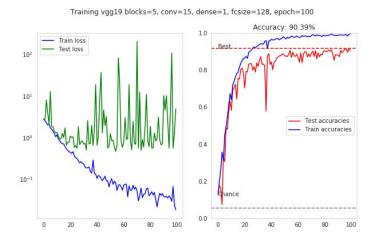


Image size (128,128)

#### Xception: Experiments

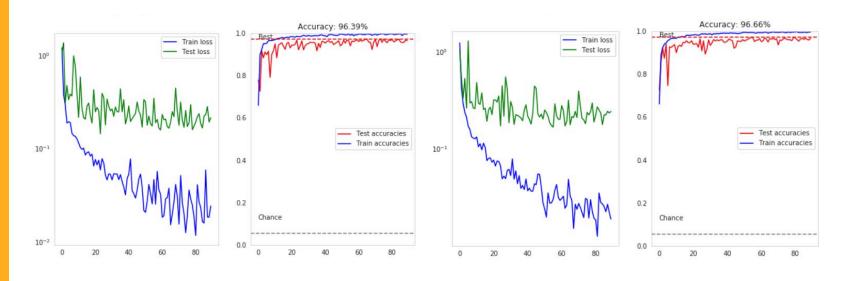


Image size (128,128) No augmentation

Image size (256,256) With augmentation

#### Best Model: Loss Curve

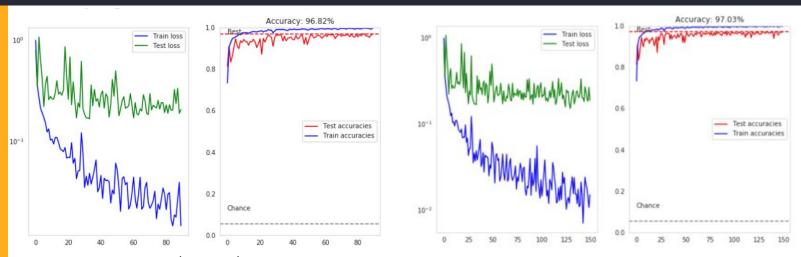


Image size: (128,128)

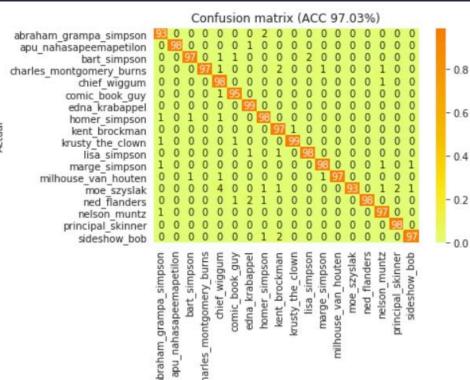
Augmentation:

randomly shift images horizontally and vertically

flip images horizontally

Test loss curve stabilized after  $\sim 50$  epochs and test accuracy achieved 97.03% after 150 epochs

#### Best Model: Confusion Matrix



Predicted

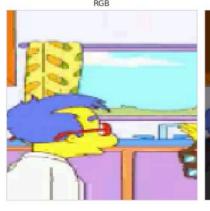
Performed well in general
Relatively poorly on:
Grampa Simpson
(often confused
with Homer Simpson)

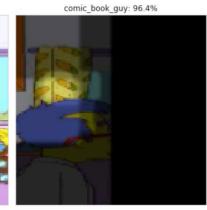


#### Best Model: Heatmap









**Correct Classification** 

Misclassification

Most of the time, the model focusing on the correct part of the image

The model was unable to classify correctly when dissecting background

#### Part II - Object Detection and Classification

#### **Evaluation** metrics

Model level

Accuracy score = number of accurately classified characters / actual number of bounding boxes

Character level

Precision: fraction of relevant characters among the retrieved instances

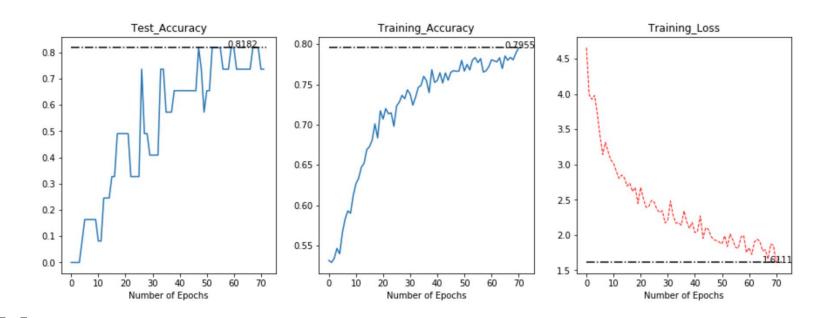
true positive cases / predicted positive cases

Recall: fraction of total amount of relevant characters that were actually retrieved

true positive cases / actual positive cases

F1-score: a special weighted average of precision and recall

#### Best Model: Fast R-CNN







#### Test Metrics Performance - Top Six Accurate Characters

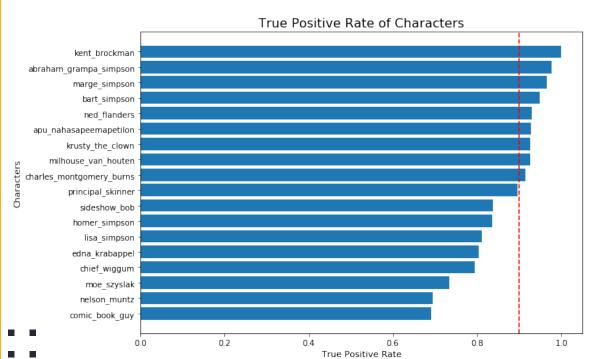
Character	Precision	Recall	F1 score
ned_flanders	0.913	0.929	0.921
marge_simpson	0.832	0.966	0.894
kent_brockman	0.800	1.000	0.889
principal_skinner	0.870	0.895	0.883
krusty_the_clown	0.826	0.927	0.874
chief_wiggum	0.939	0.795	0.861





#### Test Metrics Performance - Bottom Six Accurate Characters

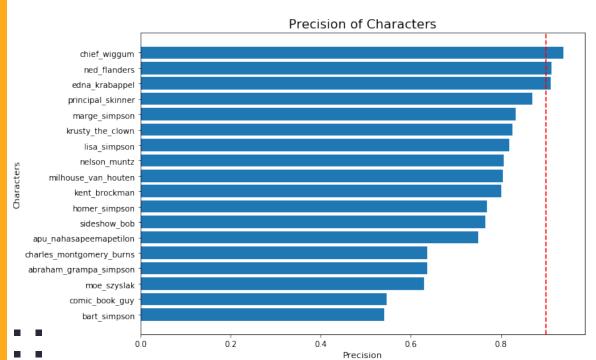
Character	Precision	Recall	F1 score
abraham_grampa_simpson	0.636	0.977	0.771
charles_montgomery_burns	0.637	0.914	0.751
nelson_muntz	0.806	0.694	0.746
bart_simpson	0.541	0.949	0.689
moe_szyslak	0.629	0.733	0.677
comic_book_guy	0.547	0.690	0.611



Half of the characters have recall greater than 90%.

The characters from Simpson Family (Marge, Bart, etc.) are highly likely to be identified.

The ranks of Simpson characters do not show significant difference.

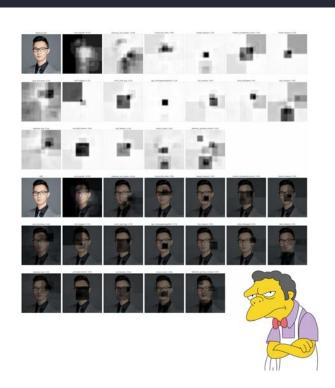


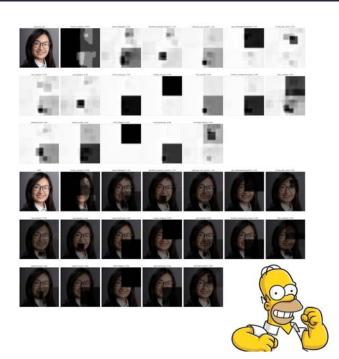
Only three characters have precision greater than 90%.

Some major characters (Bart Simpson) only have precision below 60%.

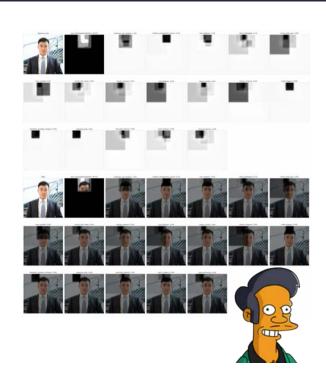
The model tends to predict more boxes as the major characters such as Bart Simpson and Abraham Grampa Simpson.

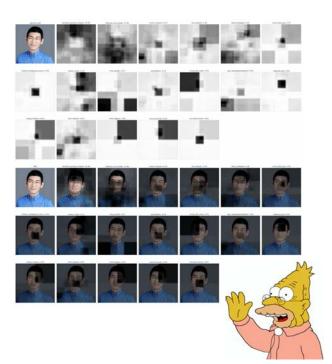
## Easter Egg



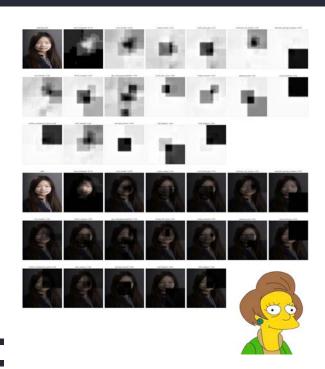


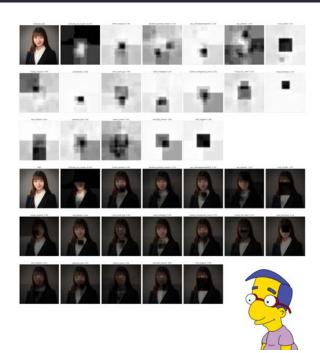
### Easter Egg





## Easter Egg





#### Conclusion - Classification

Great performance for classification (Part I)

Misclassification due to multiple characters in the same image

CNN algorithms play an important role.

#### Conclusion - Detection

Good performance for detection (Part II)

Errors due to missing bounding box labels in the pictures.

Training and predicting takes incredibly long

#### Application

Real time TV show character detection for people not good at remembering names



#### Future Opportunities

Faster Algorithm: YOLO (v4)

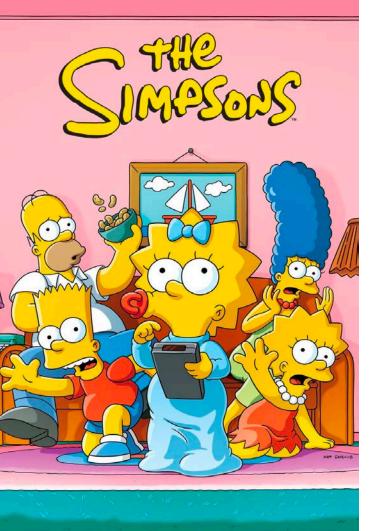




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## Thanks!

Any questions?



