

# Machine Learning for Fashion Analysis

Practical application of fashion recognition using Deep Neural Networks



# Fashion Analysis

*"Half the money I spend on advertising is wasted; the trouble is I don't know which half."* – John Wanamaker, 1922



## Problem In fashion retail

- *What are customers interested in?*
- *How can I convince the customer to buy my products?*

## Machine Learning Solution:

- ▶ Let's build a fashion image analyzer, to analyze existing fashions and better reach the customer through targeted advertising

## Challenges:

- *What is important in the image?*
- *What should the ML model recognize?*
- *How can the ML model distinguish between a "Shirt" and a "Blouse"?*

**Conclusion:** A ML model needs to understand the key characteristics to analyze

# Fashion Analysis

## Example usage:

### Classic Retail



Customer approaches store

### Online Retail

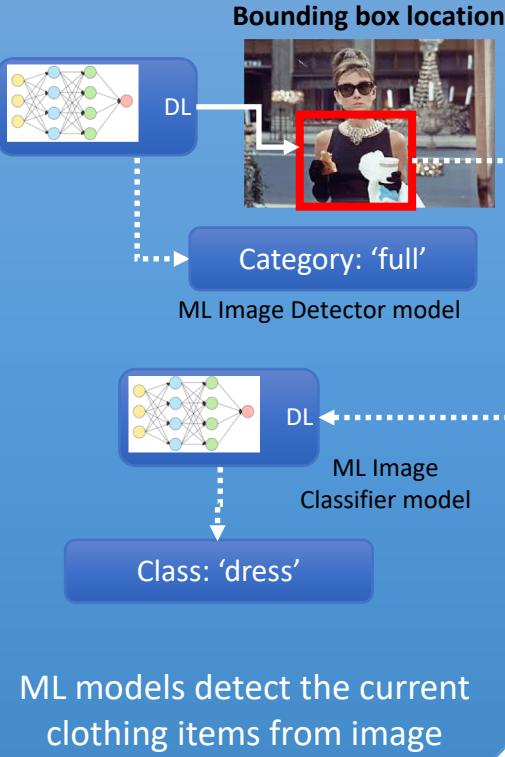


Customer uploads

\*1

\*2

\*3



### "My Boutique"

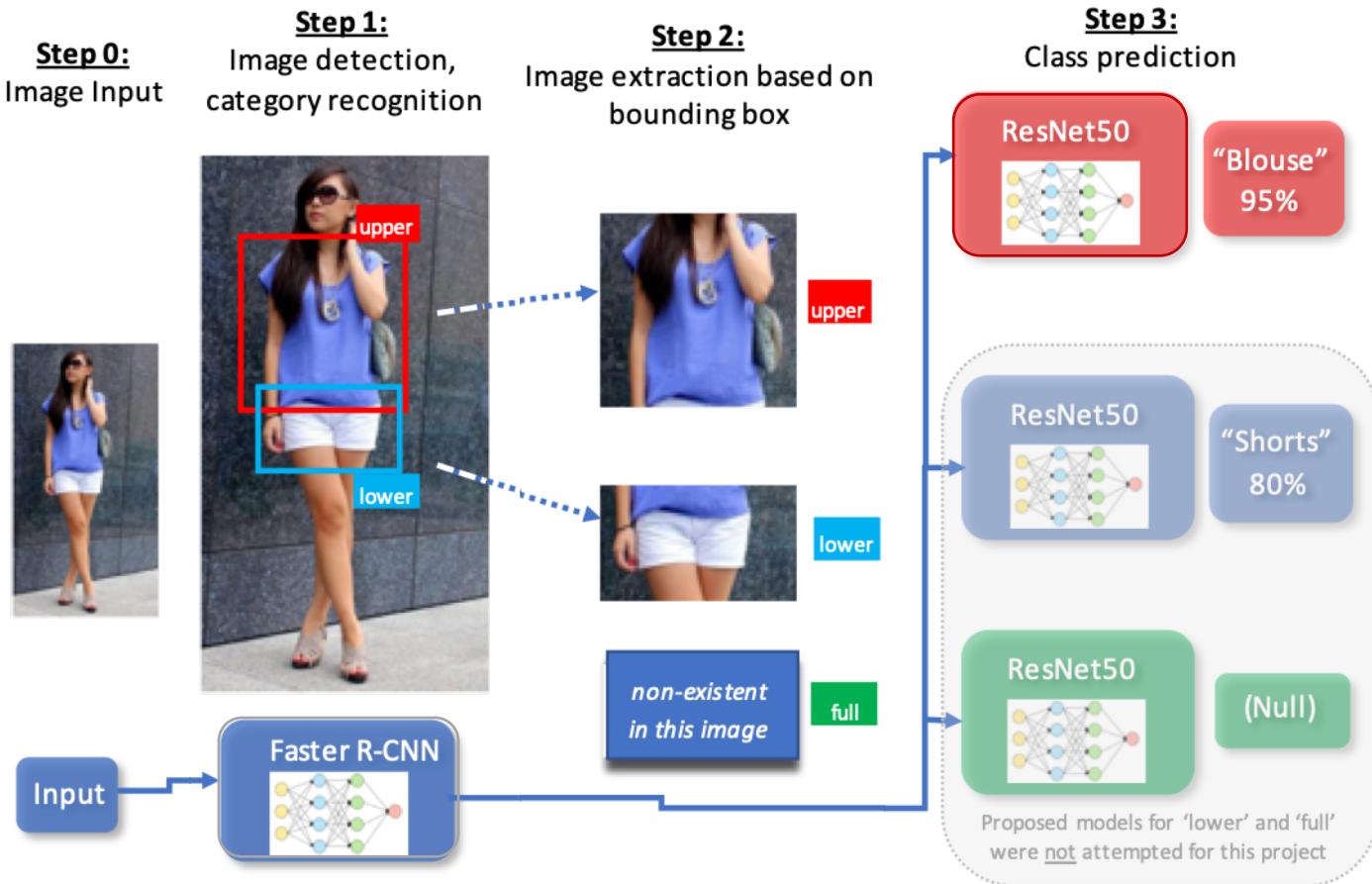


Match current pattern, recommend possible interesting items for customer from store

**Use Case:** Evaluation of image for fashion recommendation

# Fashion Analysis Models

**Solution:** Separate detection and classification tasks into separate models



By reducing complexity into separate tasks, a better result can be achieved

A multi-model approach was selected for analysis:

- Image Detector: "Faster R-CNN" based model
- Image Classifier: "ResNet50" based models

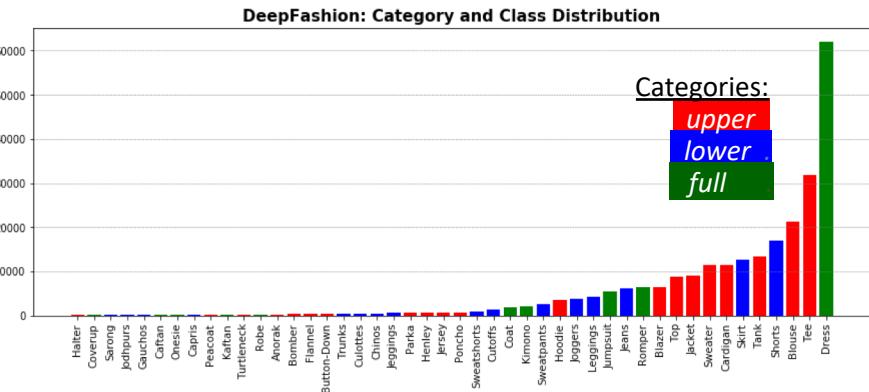
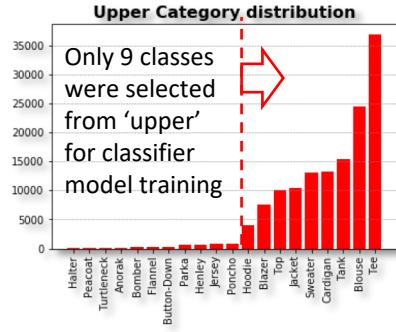
# Fashion Datasets

**DeepFashion:**  
training dataset of fashion items

*DeepFashion*<sup>1</sup>



289k fashion images,  
46 classes with bounding box annotations  
Mostly curated fashion images



Training the models used only curated images  
Testing models sets used both curated and “in-the-wild” type images

**StreetStyle:**  
test dataset for fashion “in the wild”

*StreetStyle*<sup>2</sup>

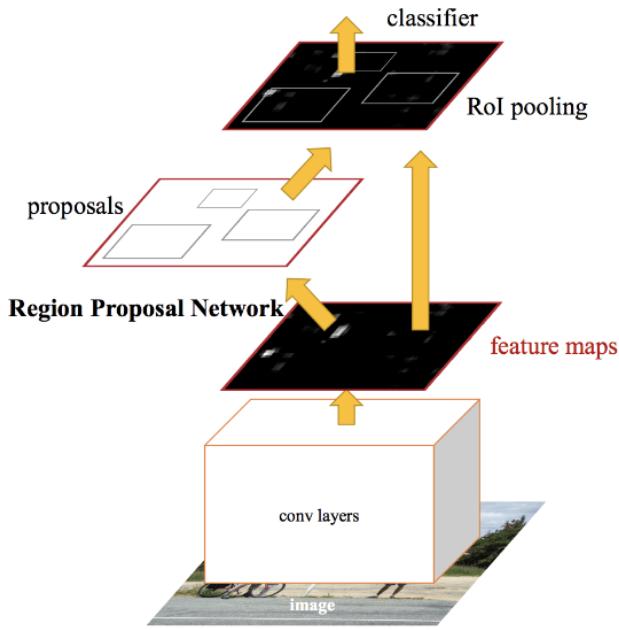


27k face & torso images  
5 classes with bounding box annotation  
Fashion images “in-the-wild”

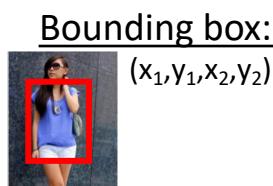


# Image Detector: *Faster R-CNN*

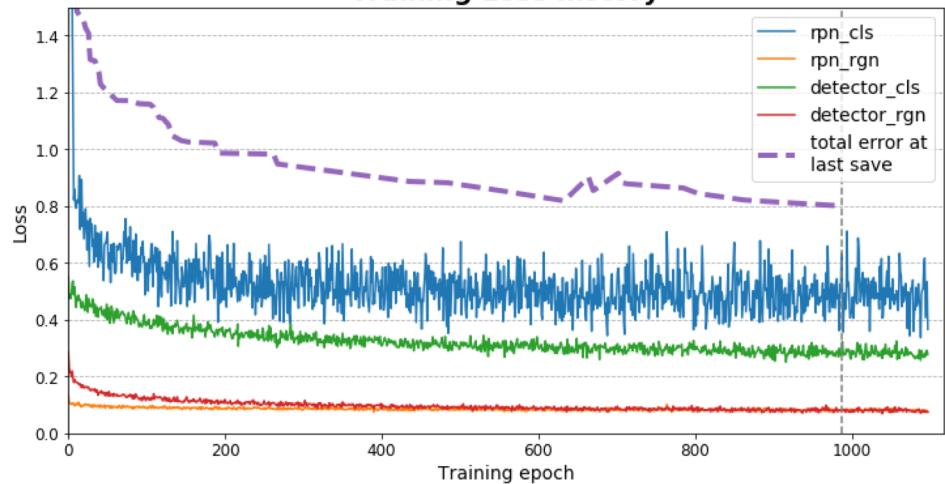
## Image Detector model: “Faster R-CNN” architecture



- Categories:
- ‘upper’
  - ‘lower’
  - ‘full’



**Image Detector (Faster R-CNN)  
Training Loss history**



**Image Detector (Faster R-CNN)  
Training Accuracy history**

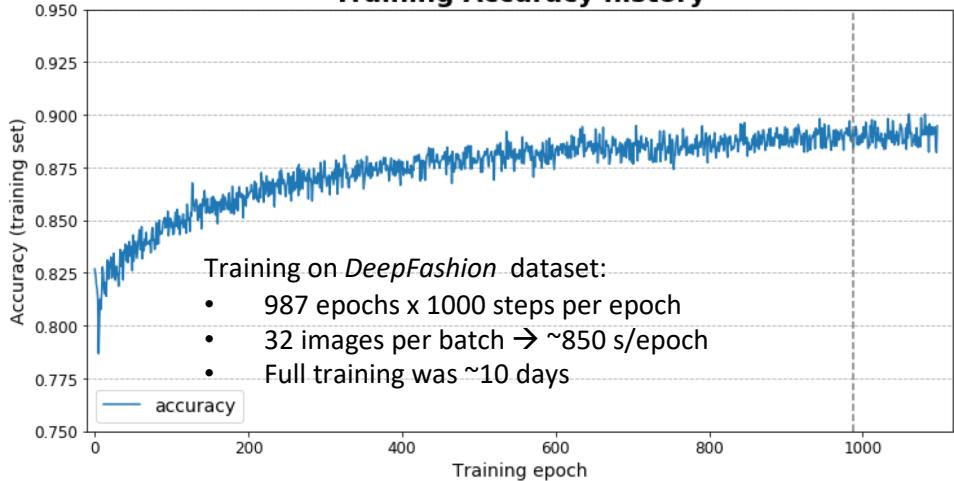


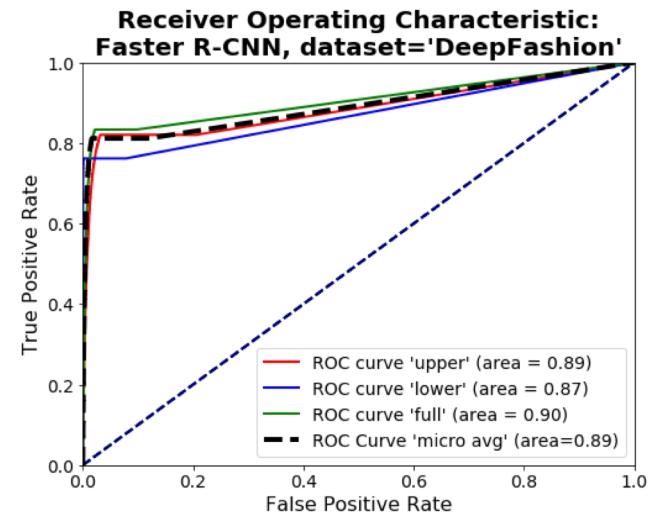
Image detector model was trained for 3 categories with bounding box information

# Image Detector: Faster R-CNN

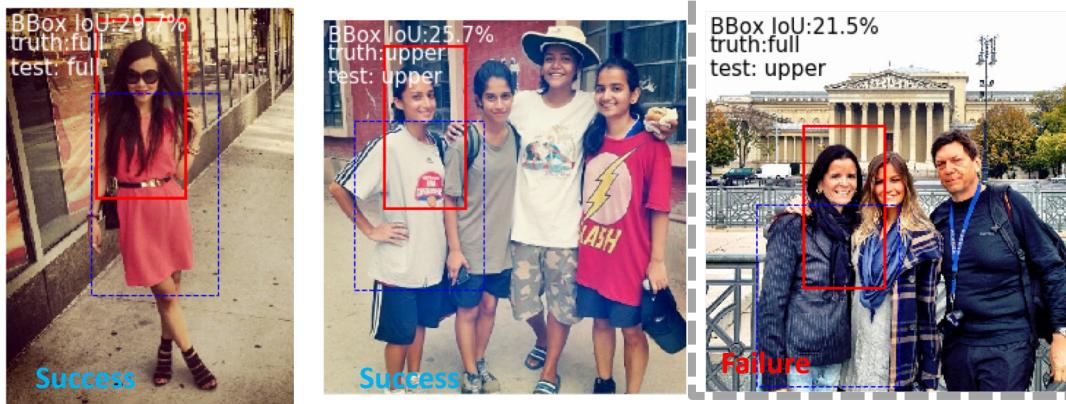
DeepFashion:



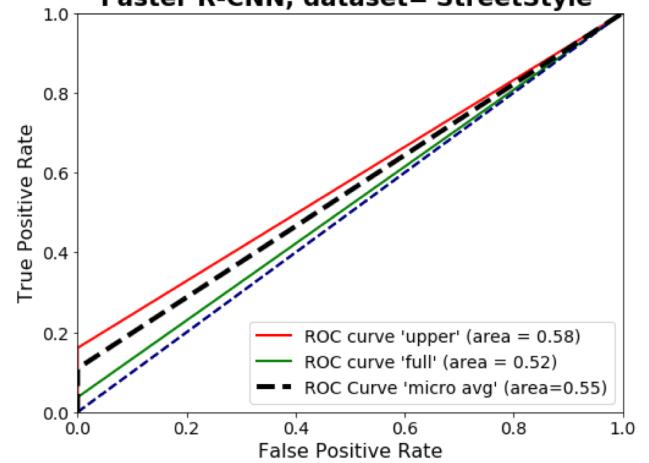
Overall Results of test datasets



StreetStyle:



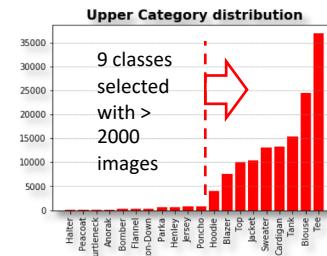
Receiver Operating Characteristic:  
Faster R-CNN, dataset='StreetStyle'



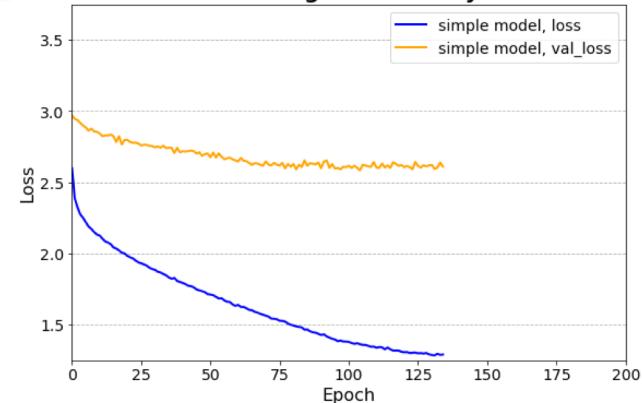
# Image Detector: *ResNet50*

## Image Classifier models:

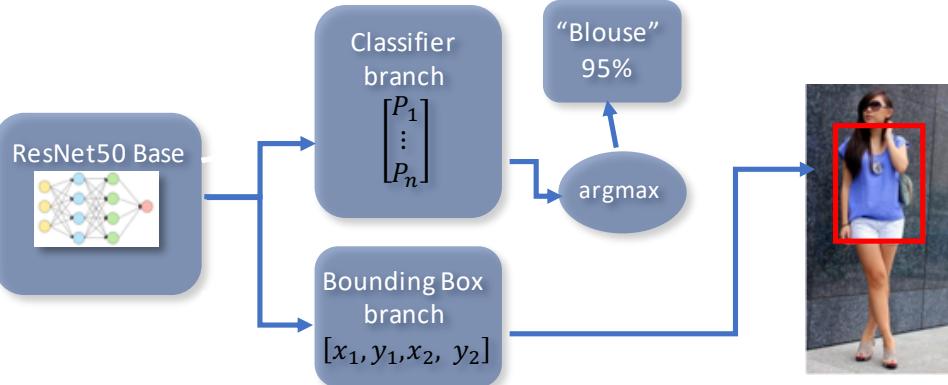
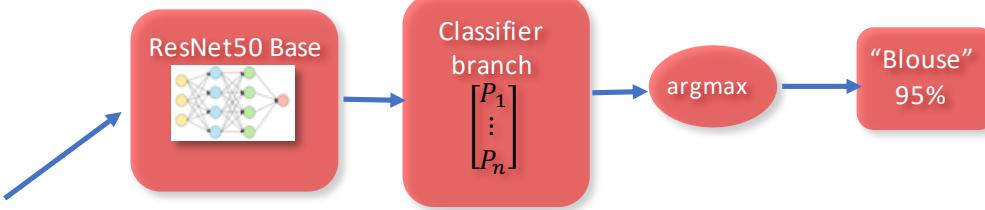
“ResNet50” architecture with and without bounding box entrainment



Simple Classifier ‘img’ (ResNet50)  
Training Loss History



Simple classifier ‘img’



Feature classifier ‘img+bbox’

Feature Classifier ‘img+bbox’ (ResNet50)  
Training Loss History

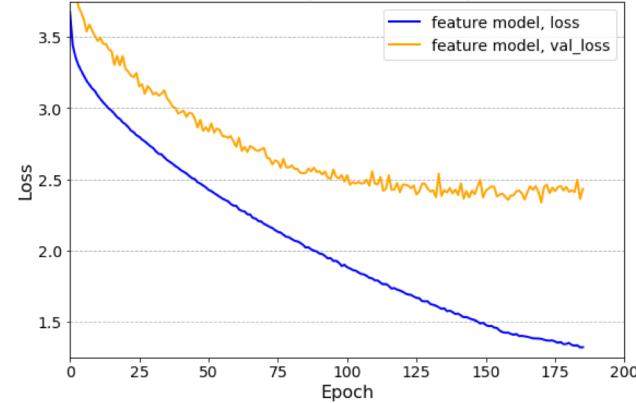


Image Classifier ‘img’ and ‘img+bbox’ models were both attempted to determine the influence of feature inclusion in model training

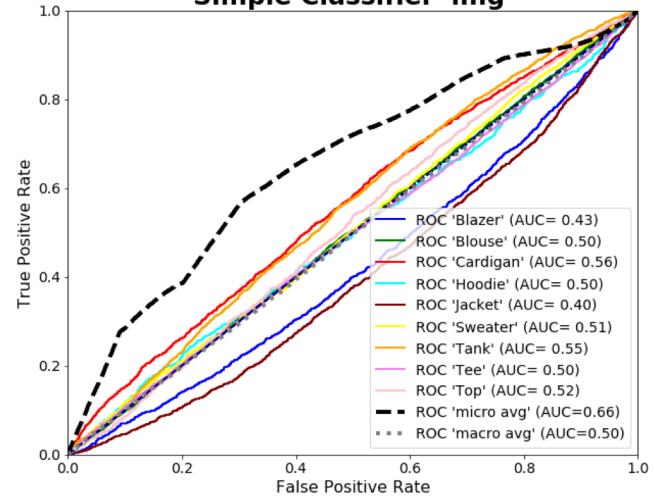
# Image Classifier: ResNet50

## Simple Classifier 'img'

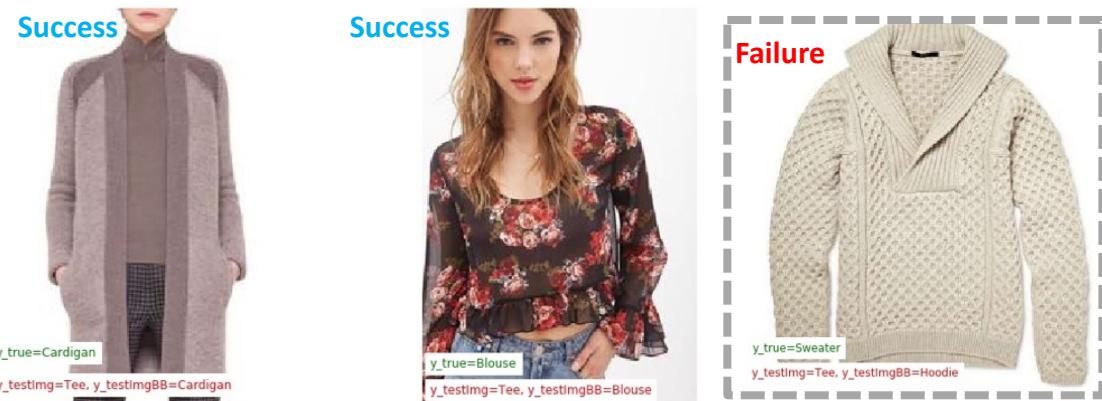


## Overall Results of test datasets

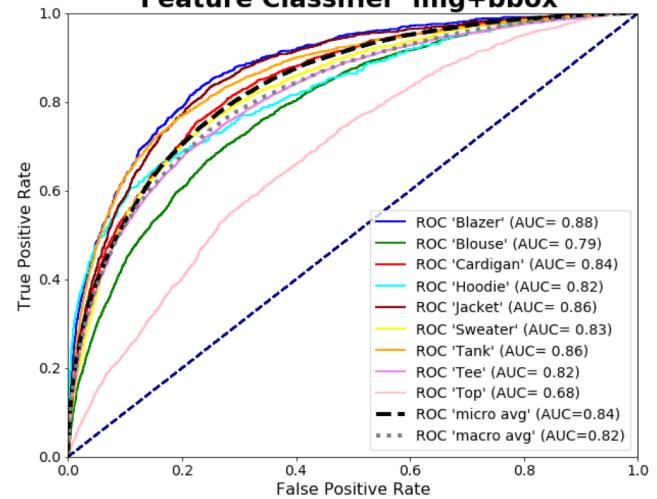
### Receiver Operating Characteristic: Simple Classifier 'img'



## Feature Classifier 'img+bbox'



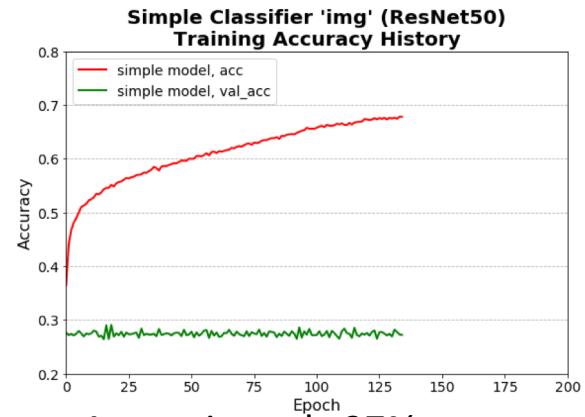
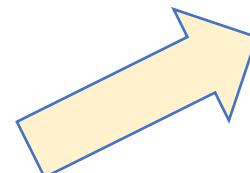
### Receiver Operating Characteristic: Feature Classifier 'img+bbox'



# Image Detector: *ResNet50*

*What went wrong with the Simple Classifier ('img') ?*

class	images class in test set	Case 1				Case 2		Case 3		Case 4		'img' model correct	'img+bbox' model correct
		y_test_Img == y_true, y_test_ImgBB == y_true	y_test_Img != y_true, y_test_ImgBB != y_true	y_test_Img == y_true, y_test_ImgBB != y_true	y_test_Img != y_true, y_test_ImgBB == y_true	y_test_Img == y_true, y_test_ImgBB != y_true	y_test_Img != y_true, y_test_ImgBB == y_true	y_test_Img == y_true, y_test_ImgBB != y_true	y_test_Img != y_true, y_test_ImgBB == y_true	y_test_Img == y_true, y_test_ImgBB != y_true	y_test_Img != y_true, y_test_ImgBB == y_true		
Blazer	1040	0	491	0	549	0	549 (53%)						
Blouse	3389	0	1941	0	1448	0	1448 (43%)						
Cardigan	1828	0	766	0	1062	0	1062 (58%)						
Hoodie	541	0	358	0	183	0	183 (34%)						
Jacket	1473	0	1239	0	234	0	234 (16%)						
Sweater	1822	0	1353	0	469	0	469 (26%)						
Tank	2097	0	1284	0	813	0	813 (20%)						
Tee	5143	3293	0	1850	0	5143 (100%)	3293 (64%)						
Top	1387	0	1084	0	303	0	303 (22%)						
<b>Totals</b>	<b>18720</b>	<b>3293</b>	<b>8516</b>	<b>1850</b>	<b>5061</b>	<b>5143 (27%)</b>	<b>8354 (45%)</b>						



Approximately 27% accuracy  
which is equal to  $N_{\text{Tee}} / N_{\text{total}}$

*...the Simple Classifier minimized its error by choosing the majority class for every prediction. The resulting model is useless for prediction...*

By better feature engineering, more attributes can be linked with the image aspects and thus lead to better model predictions

# Conclusions

*What is important for fashion image analysis?*

*...Datasets:*

- *A well-balanced class distribution is as important as number of samples*
- *A model trained on curated images will learn to predict only curated images...a better model will be trained on images as you wish to detect them (“in-the-wild”)*
- *However, make sure there is something to learn from the images (“annotations”)*

*...Models:*

- *In general, a model which addresses more features ('breadth') will outperform a complicated model ('depth') which does not address the features of the image.*
- *Be sure to check the end results, to make sure your model didn't take a 'lazy' approach (i.e. guess the majority class)*

# Questions?



Original clip: "Breakfast at Tiffany's"  
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