Automatic Understanding and Classification of Image Advertisements

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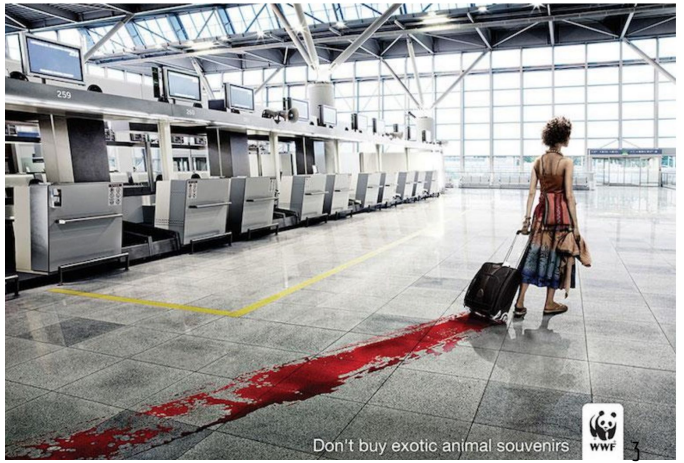
Outline

- Advertisements and their applications
- Recent work on understanding advertisements
  - Problem
  - Dataset
  - Experiments
- Our project goals

Understanding Advertisements

- Convey message to viewer
- Ads may include images and/or text
- Ads may use visual rhetoric:
  - Symbolism
  - Inference
  - Non-photorealistic objects



Applications

- Predict how effective a certain ad will be
- Better ad targeting according to user interests
- Source of revenue for companies
- Motivate the user to buy/try the product

Recent work

A recent CVPR conference paper:
“Automatic Understanding of Image and Video Advertisements” (CVPR 2017), Hussain et al.

- Link to the paper- http://people.cs.pitt.edu/~kovashka/hussain_zhang_kovashka_ads_cvpr2017.pdf
- Proposes a novel problem of understanding advertisements
- Introduces a newly created dataset to tackle this problem
- Include baseline classification results from initial experiments

Why ads?

- Why is this an important problem?
  - Part of our culture
  - Ads generate revenue
- Why is it interesting?
  - Ads convey a persuasive message
  - Many ads require decoding of their meaning
    - What, how and why

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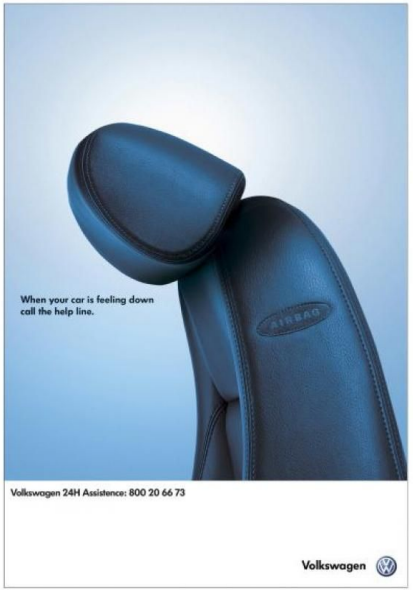
    - What, why, and how

Dataset

- 64,832 image ads
- Product ads and public service announcements (PSA)
- Annotations:
  - Product or subject of the ad
  - Sentiment attempts to inspire
  - Strategy used to convey message
  - Symbolism used
  - Answers to questions:
    - “What should the viewer do according to this ad?”
    - “Why should he/she do it?”

Initial Experiments

- Topic classification
- Sentiment classification
- Symbolism prediction model
- Question-answering

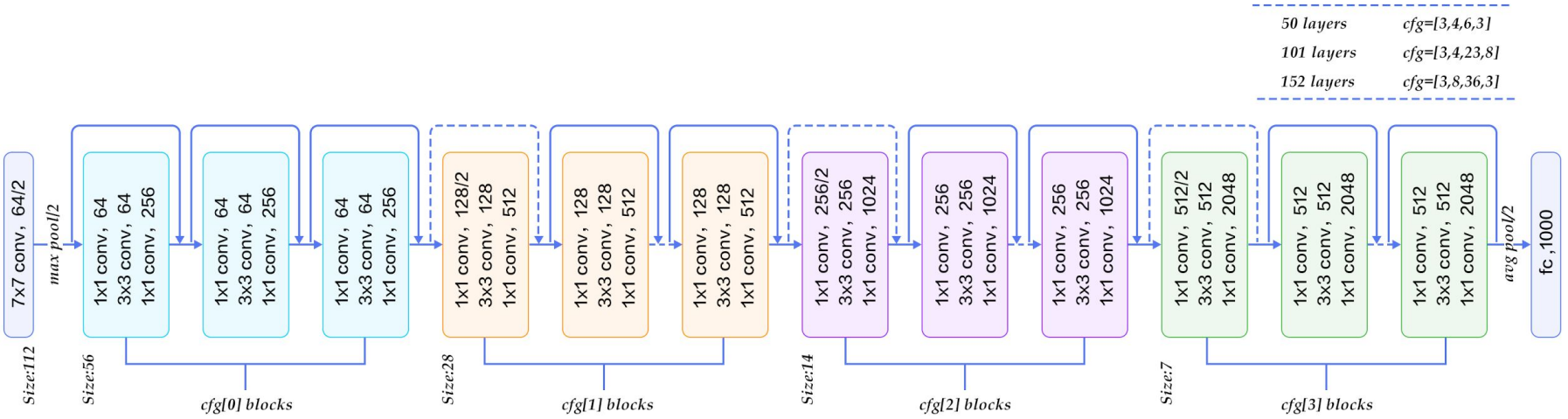


Topic and Sentiment: Dataset Annotations

Topic	Sentiment
Restaurants, cafe, fast food	Active (energetic, etc.)
Coffee, tea	Alarmed (concerned, etc.)
Sports equipment, activities	Amazed (excited, etc.)
Phone, TV and web providers	Angry (annoyed, irritated)
Education	Cheerful (delighted, etc.)
Beauty products	Disturbed (disgusted, shocked)
Cars, automobiles	Educated (enlightened, etc.)
Political candidates	Feminine (womanly, girlish)
Animal rights, animal abuse	Persuaded (impressed, etc.)
Smoking, alcohol abuse	Sad (depressed, etc.)

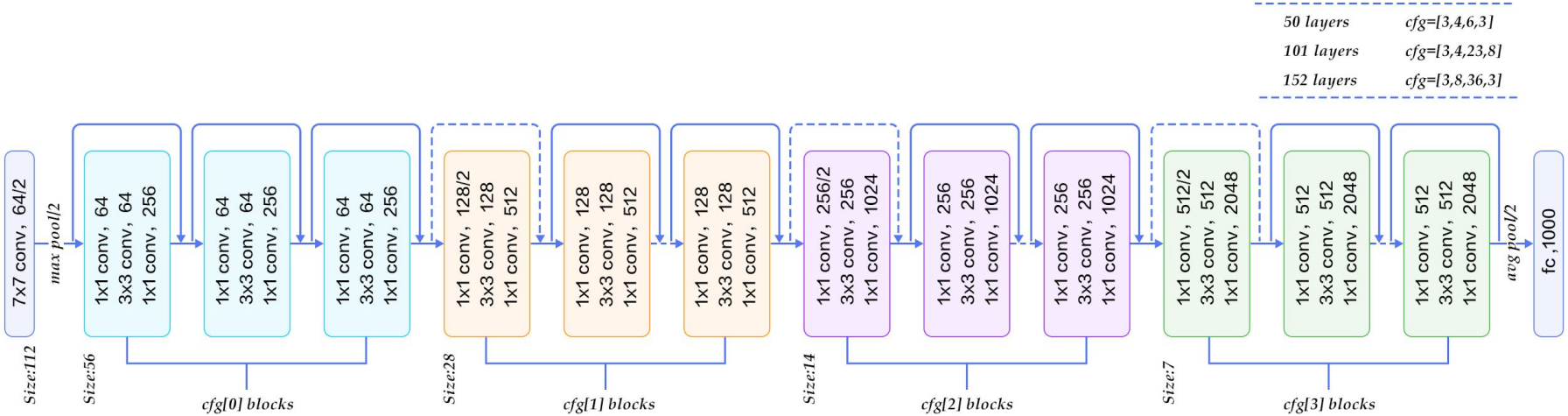
Table 2: A sample from our list of topics and sentiments. See supp for the full list of 38 topics and 30 sentiments.

Topic and sentiment: Experiment



ResNet - 152 layers

Topic and sentiment: Experimental Results



38 topics and 30 sentiments
Topics - 60.34% accuracy
Sentiment - 27.92% accuracy

Proposed Goals

- MUST goal: Use transfer learning on a new architecture (VGG), and compare performance to ResNet model results in the paper
- Bonus goal : Compare how the model works using Random Decision Forests.

Ads Dataset

Steps

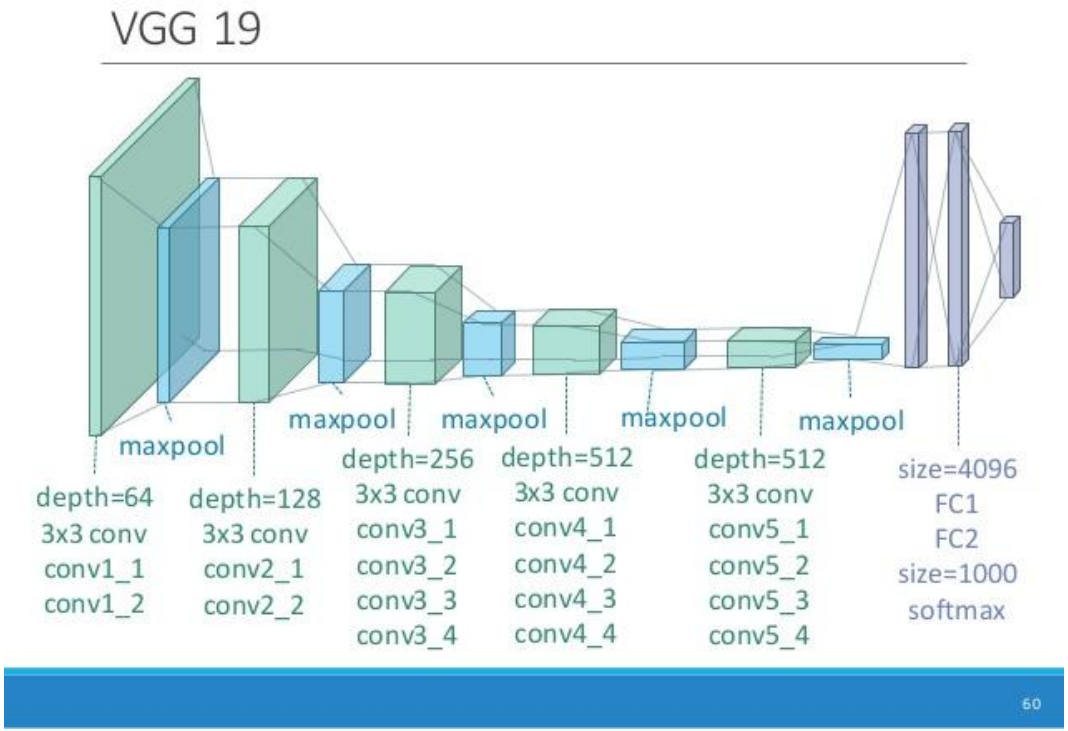
1. Load the dataset onto Maria's Machine
2. Preprocess the Image data
3. Preprocess the labels
4. Train on topic classification

Data Preprocessing

Steps

1. Preprocess the Image data
    a. VGG preprocessing with TensorFlow Slim library
    b. Resize 224 x 224
    c. Normalize
2. Preprocess the labels
    a. Select most common label (out of 3 annotations)
    b. Select one of the annotations at random

Architecture - VGG



Replace output layer with ad classes (39 total) and finetune network

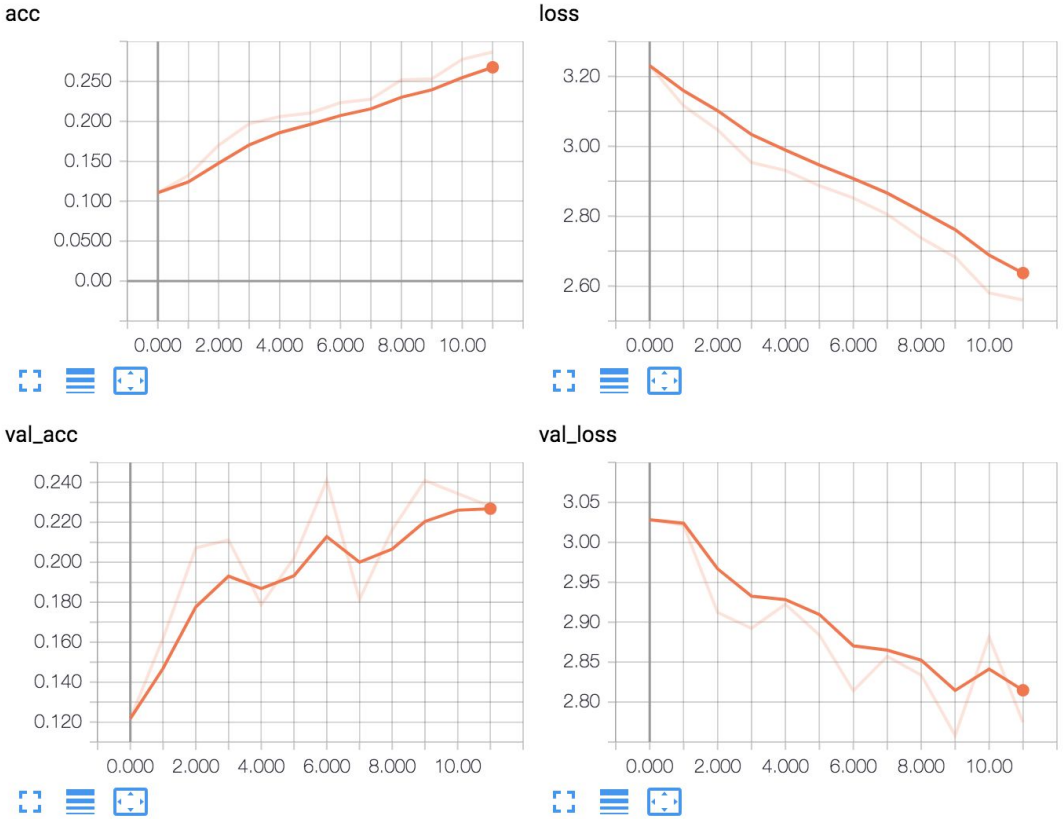
RMSProp Optimizer with Learning Rate = 0.0001

```
Start Time is :  2017-12-12 22:35:06.799926
Train on 3766 samples, validate on 772 samples
Epoch 1/12
3766/3766 [==============================] - 105s 28ms/step - loss: 3.3279 - acc: 0.1179 - val_loss: 3.2206 - val_acc: 0.0972
Epoch 2/12
3766/3766 [==============================] - 103s 27ms/step - loss: 3.0975 - acc: 0.1277 - val_loss: 2.9937 - val_acc: 0.1619
Epoch 3/12
3766/3766 [==============================] - 103s 27ms/step - loss: 3.0156 - acc: 0.1726 - val_loss: 3.0480 - val_acc: 0.1464
Epoch 4/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.9305 - acc: 0.1997 - val_loss: 2.9531 - val_acc: 0.1865
Epoch 5/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.8858 - acc: 0.2116 - val_loss: 2.8148 - val_acc: 0.2435
Epoch 6/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.8313 - acc: 0.2265 - val_loss: 2.8418 - val_acc: 0.2409
Epoch 7/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.8195 - acc: 0.2326 - val_loss: 2.8944 - val_acc: 0.2474
Epoch 8/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.7857 - acc: 0.2422 - val_loss: 2.8304 - val_acc: 0.2396
Epoch 9/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.7700 - acc: 0.2377 - val_loss: 2.9050 - val_acc: 0.2124
Epoch 10/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.7270 - acc: 0.2472 - val_loss: 2.8254 - val_acc: 0.2565
Epoch 11/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.7264 - acc: 0.2507 - val_loss: 2.9046 - val_acc: 0.2383
Epoch 12/12
3766/3766 [==============================] - 103s 27ms/step - loss: 2.7056 - acc: 0.2618 - val_loss: 3.0451 - val_acc: 0.1930
('End Time is : ', datetime.datetime(2017, 12, 12, 22, 55, 53, 36343))
('Total time is :', datetime.timedelta(0, 1246, 236417))
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 3.0687704319470779)
('Test accuracy:', 0.1991189429675955)
```

Adam Optimizer with Learning Rate = 0.0001

```
Epoch 2/15
3766/3766 [==============================] - 108s 29ms/step - loss: 3.0815 - acc: 0.1585 - val_loss: 3.0052 - val_acc: 0.1645
Epoch 3/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.9820 - acc: 0.1986 - val_loss: 2.9805 - val_acc: 0.1749
Epoch 4/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.9093 - acc: 0.2135 - val_loss: 2.8907 - val_acc: 0.2085
Epoch 5/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.8564 - acc: 0.2143 - val_loss: 2.8937 - val_acc: 0.1982
Epoch 6/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.7947 - acc: 0.2334 - val_loss: 2.9141 - val_acc: 0.1917
Epoch 7/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.7448 - acc: 0.2435 - val_loss: 2.8510 - val_acc: 0.2124
Epoch 8/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.6910 - acc: 0.2520 - val_loss: 3.0387 - val_acc: 0.1632
Epoch 9/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.6560 - acc: 0.2637 - val_loss: 2.8100 - val_acc: 0.2370
Epoch 10/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.5787 - acc: 0.2831 - val_loss: 2.8412 - val_acc: 0.2306
Epoch 11/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.5077 - acc: 0.3056 - val_loss: 2.8120 - val_acc: 0.2539
Epoch 12/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.4449 - acc: 0.3197 - val_loss: 2.7898 - val_acc: 0.2604
Epoch 13/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.3418 - acc: 0.3542 - val_loss: 2.9007 - val_acc: 0.2241
Epoch 14/15
3766/3766 [==============================] - 108s 29ms/step - loss: 2.1961 - acc: 0.3720 - val_loss: 2.9365 - val_acc: 0.2526
Epoch 15/15
3766/3766 [==============================] - 108s 29ms/step - loss: 1.9915 - acc: 0.4376 - val_loss: 3.0221 - val_acc: 0.2539
('End Time is : ', datetime.datetime(2017, 12, 12, 19, 2, 25, 238472))
('Total time is :', datetime.timedelta(0, 1630, 607568))
Saved trained model at /home/micha/project/model4/saved_models/model4_trained.h5
2017-12-12 19:02:26.703793: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 3.45GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 3.0253931039230415)
('Test accuracy:', 0.25286343635966602)
```

Adam Optimizer with Learning Rate = 0.0001

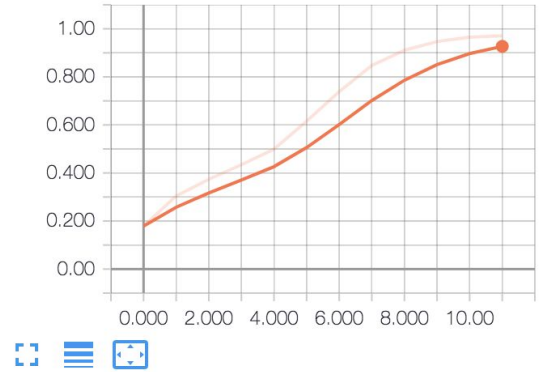


Adam Optimizer with Learning Rate = 0.00001

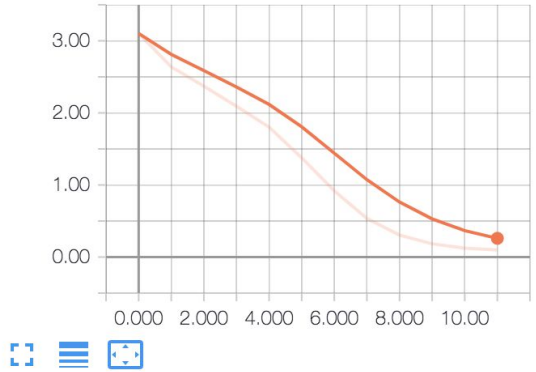
```
Epoch 1/12
2017-12-12 21:19:23.330449: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 2.20GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
2017-12-12 21:19:23.552824: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 2.20GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
2017-12-12 21:19:23.658456: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 2.20GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
2017-12-12 21:19:23.701682: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 2.15GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
3766/3766 [==============================] - 111s 30ms/step - loss: 3.1024 - acc: 0.1792 - val_loss: 2.7488 - val_acc: 0.2927
Epoch 2/12
3766/3766 [==============================] - 109s 29ms/step - loss: 2.6389 - acc: 0.3040 - val_loss: 2.5415 - val_acc: 0.3446
Epoch 3/12
3766/3766 [==============================] - 109s 29ms/step - loss: 2.3705 - acc: 0.3736 - val_loss: 2.5275 - val_acc: 0.3549
Epoch 4/12
3766/3766 [==============================] - 109s 29ms/step - loss: 2.0919 - acc: 0.4341 - val_loss: 2.4528 - val_acc: 0.3705
Epoch 5/12
3766/3766 [==============================] - 109s 29ms/step - loss: 1.8028 - acc: 0.4992 - val_loss: 2.4536 - val_acc: 0.3795
Epoch 6/12
3766/3766 [==============================] - 109s 29ms/step - loss: 1.3769 - acc: 0.6152 - val_loss: 2.6018 - val_acc: 0.3653
Epoch 7/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.9188 - acc: 0.7384 - val_loss: 3.0846 - val_acc: 0.3562
Epoch 8/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.5369 - acc: 0.8471 - val_loss: 3.2896 - val_acc: 0.3640
Epoch 9/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.3051 - acc: 0.9108 - val_loss: 3.5646 - val_acc: 0.3303
Epoch 10/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.1839 - acc: 0.9472 - val_loss: 3.9702 - val_acc: 0.3225
Epoch 11/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.1238 - acc: 0.9655 - val_loss: 4.5174 - val_acc: 0.3446
Epoch 12/12
3766/3766 [==============================] - 109s 29ms/step - loss: 0.0989 - acc: 0.9713 - val_loss: 4.2416 - val_acc: 0.3290
('End Time is : ', datetime.datetime(2017, 12, 12, 21, 41, 14, 922509))
('Total time is :', datetime.timedelta(0, 1317, 157020))
2017-12-12 21:41:15.056716: W tensorflow/core/common_runtime/bfc_allocator.cc:217] Allocator (GPU_0_bfc) ran out of memory trying to allocate
 3.45GiB. The caller indicates that this is not a failure, but may mean that there could be performance gains if more memory is available.
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 3.9368848930896641)
('Test accuracy:', 0.35330396523034518)
```

Adam Optimizer with Learning Rate = 0.00001

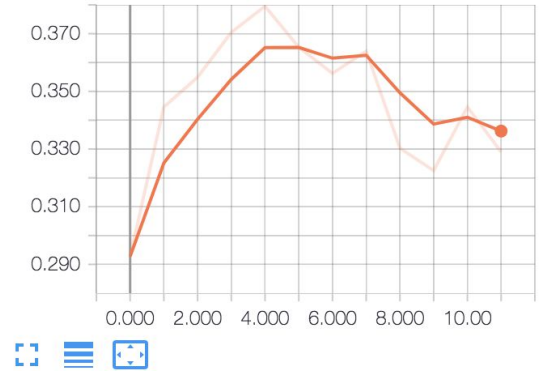
acc



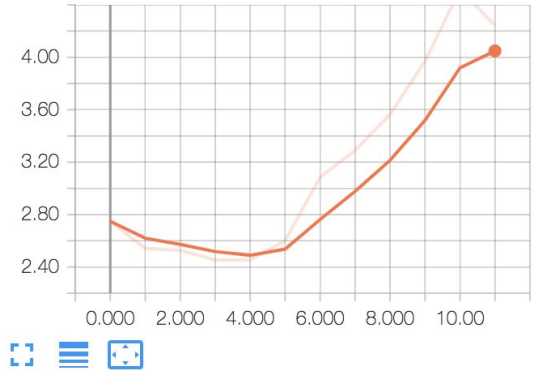
loss



val_acc



val_loss



Stochastic Gradient Descent Optimizer with Learning Rate= 0.00001

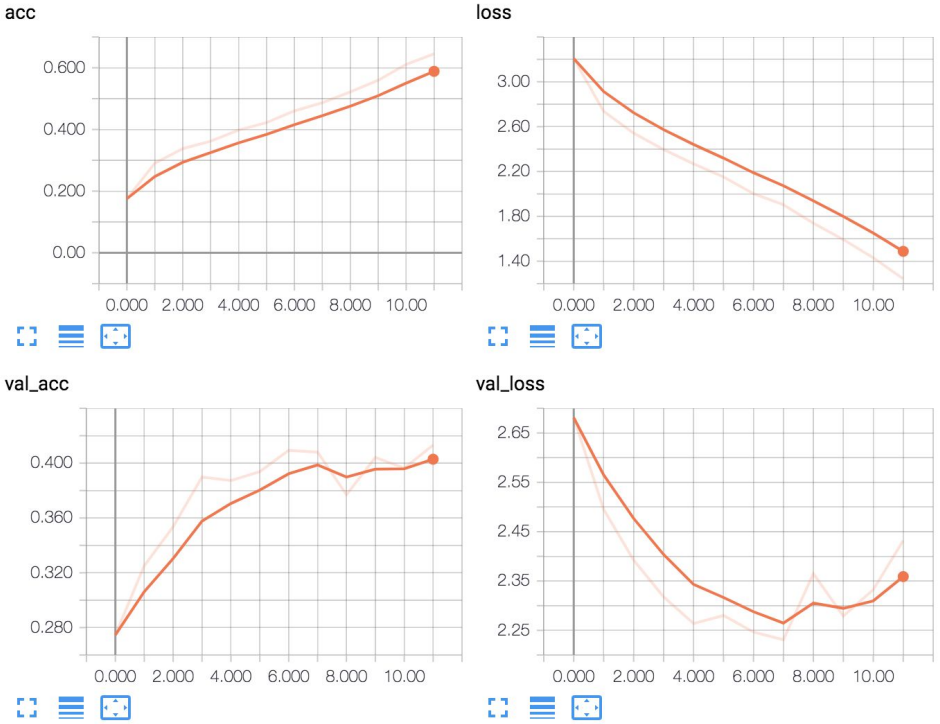
```
Epoch 1/12
3766/3766 [==============================] - 101s 27ms/step - loss: 3.6982 - acc: 0.0929 - val_loss: 2.9960 - val_acc: 0.1891
Epoch 2/12
3766/3766 [==============================] - 98s 26ms/step - loss: 3.3032 - acc: 0.1267 - val_loss: 2.9586 - val_acc: 0.2228
Epoch 3/12
3766/3766 [==============================] - 99s 26ms/step - loss: 3.2025 - acc: 0.1426 - val_loss: 2.9051 - val_acc: 0.2034
Epoch 4/12
3766/3766 [==============================] - 99s 26ms/step - loss: 3.1278 - acc: 0.1569 - val_loss: 2.8598 - val_acc: 0.2396
Epoch 5/12
3766/3766 [==============================] - 99s 26ms/step - loss: 3.0382 - acc: 0.1880 - val_loss: 2.8004 - val_acc: 0.2578
Epoch 6/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.9609 - acc: 0.2130 - val_loss: 2.7421 - val_acc: 0.2772
Epoch 7/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.9267 - acc: 0.2302 - val_loss: 2.6947 - val_acc: 0.2824
Epoch 8/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.8517 - acc: 0.2454 - val_loss: 2.6448 - val_acc: 0.3070
Epoch 9/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.7993 - acc: 0.2589 - val_loss: 2.6187 - val_acc: 0.3135
Epoch 10/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.7676 - acc: 0.2716 - val_loss: 2.5723 - val_acc: 0.3238
Epoch 11/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.7014 - acc: 0.2804 - val_loss: 2.5512 - val_acc: 0.3290
Epoch 12/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.6746 - acc: 0.2942 - val_loss: 2.5327 - val_acc: 0.3238
('End Time is : ', datetime.datetime(2017, 12, 13, 1, 22, 32, 796516))
('Total time is :', datetime.timedelta(0, 1189, 996458))
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 2.6412126566344947)
('Test accuracy:', 0.30484581521429155)
```

Stochastic Gradient Descent Optimizer with Learning Rate= 0.0001

```
evice: 0, name: GeForce GTX 1080, pci bus id: 0000:01:00.0)
Start Time is :  2017-12-12 23:04:37.244193
Train on 3766 samples, validate on 772 samples
Epoch 1/12
3766/3766 [==============================] - 100s 27ms/step - loss: 3.2076 - acc: 0.1753 - val_loss: 2.6811 - val_acc: 0.2746
Epoch 2/12
3766/3766 [==============================] - 98s 26ms/step - loss: 2.7367 - acc: 0.2902 - val_loss: 2.4951 - val_acc: 0.3251
Epoch 3/12
3766/3766 [==============================] - 98s 26ms/step - loss: 2.5425 - acc: 0.3378 - val_loss: 2.3923 - val_acc: 0.3536
Epoch 4/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.3965 - acc: 0.3622 - val_loss: 2.3179 - val_acc: 0.3899
Epoch 5/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.2682 - acc: 0.3980 - val_loss: 2.2637 - val_acc: 0.3873
Epoch 6/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.1517 - acc: 0.4222 - val_loss: 2.2801 - val_acc: 0.3938
Epoch 7/12
3766/3766 [==============================] - 99s 26ms/step - loss: 2.0026 - acc: 0.4602 - val_loss: 2.2465 - val_acc: 0.4093
Epoch 8/12
3766/3766 [==============================] - 99s 26ms/step - loss: 1.9034 - acc: 0.4867 - val_loss: 2.2310 - val_acc: 0.4080
Epoch 9/12
3766/3766 [==============================] - 99s 26ms/step - loss: 1.7396 - acc: 0.5218 - val_loss: 2.3650 - val_acc: 0.3769
Epoch 10/12
3766/3766 [==============================] - 99s 26ms/step - loss: 1.5930 - acc: 0.5597 - val_loss: 2.2790 - val_acc: 0.4041
Epoch 11/12
3766/3766 [==============================] - 99s 26ms/step - loss: 1.4305 - acc: 0.6110 - val_loss: 2.3323 - val_acc: 0.3964
Epoch 12/12
3766/3766 [==============================] - 99s 26ms/step - loss: 1.2432 - acc: 0.6452 - val_loss: 2.4322 - val_acc: 0.4132
('End Time is : ', datetime.datetime(2017, 12, 12, 23, 24, 26, 957728))
('Total time is :', datetime.timedelta(0, 1189, 713535))
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 2.5353376791865814)
('Test accuracy:', 0.40176211472124779)
```

Best Model

SGD with Learning rate of 0.0001



Best Model

SGD Optimizer on VGG19 with Learning Rate = 0.001

```
('End Time is :', datetime.datetime(2017, 12, 12, 23, 24, 26, 957728))
('Total time is :', datetime.timedelta(0, 1189, 713535))
1135/1135 [==============================] - 9s 8ms/step
('Test loss:', 2.5353376791865814)
('Test accuracy:', 0.40176211472124779)
```

Training summary

Optimizer	Learning rate	Validation accuracy
RMSProp	.0001	.1930
Adam	.0001	.2539
Adam	.00001	.3290
SGD	.00001	.3238
SGD	.0001	.4132

Results

Table of Comparison

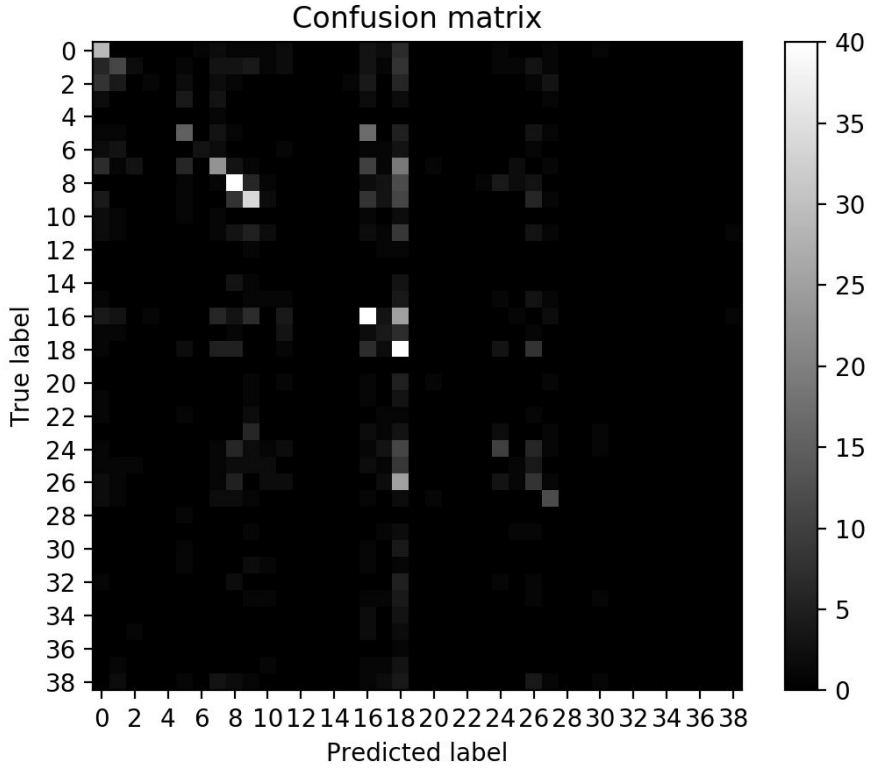
Our Model

Training Accuracy	64.52
Test Accuracy	40.173%
Model Used	VGG19
Dataset size	5673

Paper Model

Training Accuracy	N/A
Test Accuracy	60.34%
Model Used	ResNet 152-layer
Dataset size	64832

Results: Confusion Matrix



Classes

0 "Restaurants, cafe, fast food" (ABBREVIATION: "restaurant")
1 "Chocolate, cookies, candy, ice cream" (ABBREVIATION: "chocolate")
2 "Chips, snacks, nuts, fruit, gum, cereal, yogurt, soups" (ABBREVIATION: "chips")
3 "Seasoning, condiments, ketchup" (ABBREVIATION: "seasoning")
4 "Pet food" (ABBREVIATION: "petfood")
5 "Alcohol" (ABBREVIATION: "alcohol")
6 "Coffee, tea" (ABBREVIATION: "coffee")
7 "Soda, juice, milk, energy drinks, water" (ABBREVIATION: "soda")
8 "Cars, automobiles (car sales, auto parts, car insurance, car repair, gas, motor oil, etc.)" (ABBREVIATION: "cars")
9 "Electronics (computers, laptops, tablets, cellphones, TVs, etc.)" (ABBREVIATION: "electronics")
10 "Phone, TV and internet service providers" (ABBREVIATION: "phone_tv_internet_providers")
11 "Financial services (banks, credit cards, investment firms, etc.)" (ABBREVIATION: "financial")
12 "Education (universities, colleges, kindergarten, online degrees, etc.)" (ABBREVIATION: "education")
13 "Security and safety services (anti-theft, safety courses, etc.)" (ABBREVIATION: "security")
14 "Software (internet radio, streaming, job search website, grammar correction, travel planning, etc.)" (ABBREVIATION: "software")
15 "Other services (dating, tax, legal, loan, religious, printing, catering, etc.)" (ABBREVIATION: "other_service")
16 "Beauty products and cosmetics (deodorants, toothpaste, makeup, hair products, laser hair removal, etc.)" (ABBREVIATION: "beauty")
17 "Healthcare and medications (hospitals, health insurance, allergy, cold remedy, home tests, vitamins)" (ABBREVIATION: "healthcare")
18 "Clothing and accessories (jeans, shoes, eye glasses, handbags, watches, jewelry)" (ABBREVIATION: "clothing")
19 "Baby products (baby food, sippy cups, diapers, etc.)" (ABBREVIATION: "baby")
20 "Games and toys (including video and mobile games)" (ABBREVIATION: "game")
21 "Cleaning products (detergents, fabric softeners, soap, tissues, paper towels, etc.)" (ABBREVIATION: "cleaning")
22 "Home improvements and repairs (furniture, decoration, lawn care, plumbing, etc.)" (ABBREVIATION: "home_improvement")
23 "Home appliances (coffee makers, dishwashers, cookware, vacuum cleaners, heaters, music players, etc.)" (ABBREVIATION: "home_appliance")
24 "Vacation and travel (airlines, cruises, theme parks, hotels, travel agents, etc.)" (ABBREVIATION: "travel")
25 "Media and arts (TV shows, movies, musicals, books, audio books, etc.)" (ABBREVIATION: "media")
26 "Sports equipment and activities" (ABBREVIATION: "sports")
27 "Shopping (department stores, drug stores, groceries, etc.)" (ABBREVIATION: "shopping")
28 "Gambling (lotteries, casinos, etc.)" (ABBREVIATION: "gambling")
29 "Environment, nature, pollution, wildlife" (ABBREVIATION: "environment")
30 "Animal rights, animal abuse" (ABBREVIATION: "animal_right")
31 "Human rights" (ABBREVIATION: "human_right")
32 "Safety, safe driving, fire safety" (ABBREVIATION: "safety")
33 "Smoking, alcohol abuse" (ABBREVIATION: "smoking_alcohol_abuse")
34 "Domestic violence" (ABBREVIATION: "domestic_violence")
35 "Self esteem, bullying, cyber bullying" (ABBREVIATION: "self_esteem")
36 "Political candidates (support or opposition)" (ABBREVIATION: "political")
37 "Charities" (ABBREVIATION: "charities")
38 "Unclear"

Results by classes

Best performing classes

0 "Restaurants, cafe, fast food"

8 "Cars, automobiles”

9 "Electronics”

16 "Beauty products and cosmetics”

18 "Clothing and accessories”

Poorest performing classes

19 "Baby products”

36 "Political"

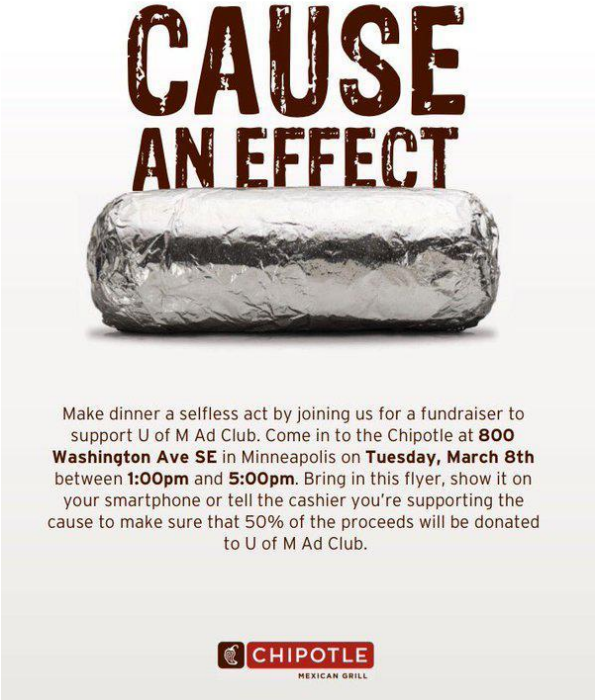
35 "Self esteem, bullying, cyber bullying"

34 "Domestic violence"

33 "Smoking, alcohol abuse"

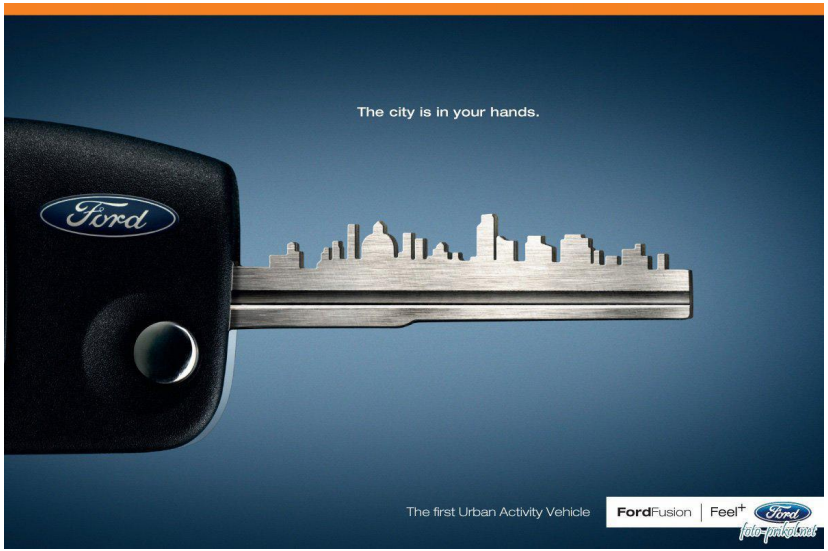
Results

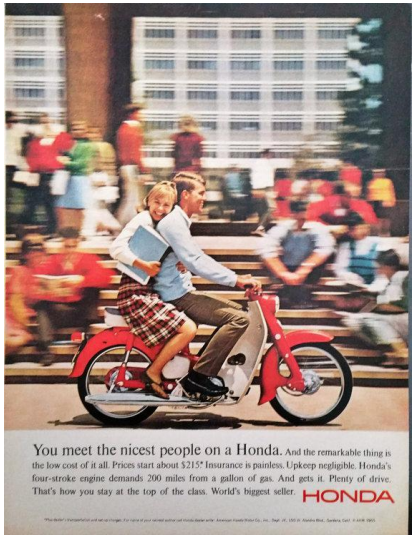
Correct ad predictions for “Restaurants, cafe, fast food” category:



Results

Correct ad predictions for “Cars, automobiles” category:





Results

Correct ad predictions for “Electronics” category:

Results

Correct ad predictions for “Beauty” category:

Results

Correct ad predictions for “Clothing and accessories” category:

Results: Incorrect Predictions

True label: "Vacation and travel”

Predicted label: "Clothing and accessories”

True label: "Restaurants, cafe, fast food"

Predicted label: "Financial services”

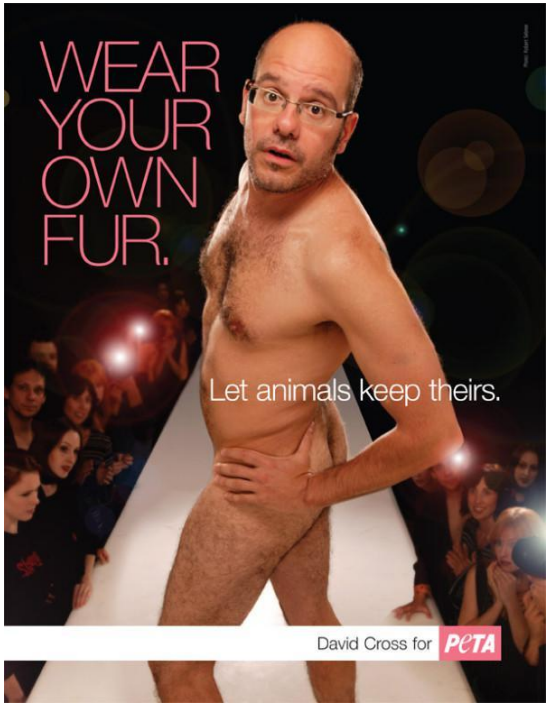
Results: Incorrect Predictions

True label: "Chocolate, cookies, candy, ice cream"

Predicted label: "Chips, snacks, nuts, fruit, gum, cereal, yogurt, soups"

Results: Incorrect Predictions

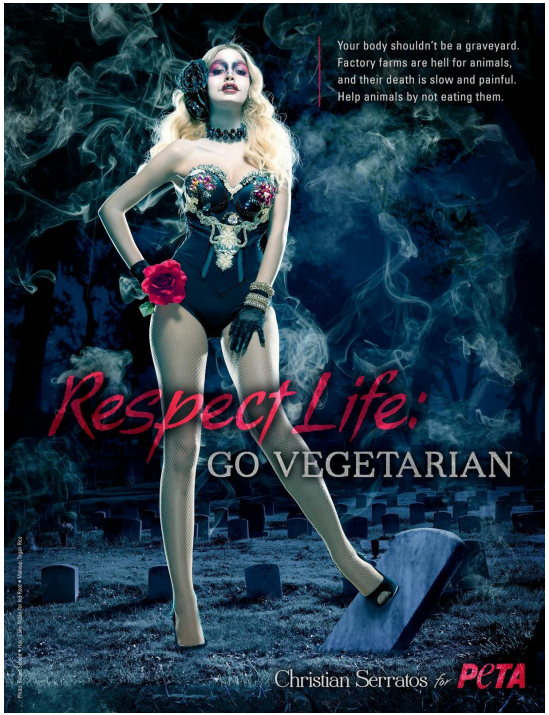
Difficulty interpreting public service announcements (PSA):



True label: "Animal rights, animal abuse"

(Left) Predicted label: "Clothing and accessories”

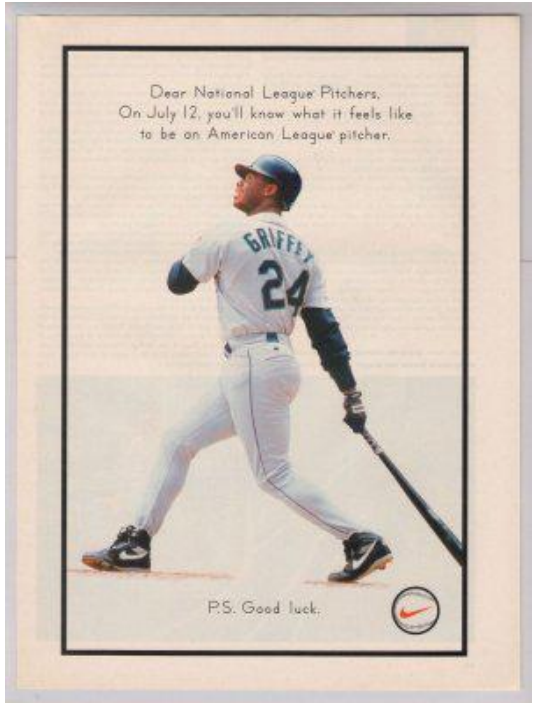
(Right) Predicted label: "Alcohol"



Results: Incorrect Predictions

Many false positives in the "Clothing and accessories" category:

True label: "Sports equipment and activities"



True label: "Self esteem, bullying, cyber bullying"

Ways to improve

1. Train on the whole dataset - we used 8.75% of the dataset
2. Try another model architecture
3. Remove “noise” from dataset - annotations aren’t all consistent
4. Add Natural Language Processing component to understand ads with text

Our Code

You can find our code on the github Repo given below.

Github Link : https://github.com/divya025/Computer-Vision

Bonus : A little about SGD and Convergence

- Stochastic gradient descent (SGD) performs a parameter update for *each* training example x(i)x(i) and label y(i)y(i).
- Batch gradient descent performs redundant computations for large datasets, as it recomputes gradients for similar examples before each parameter update. SGD does away with this redundancy by performing one update at a time. It is therefore usually much faster and can also be used to learn online.
- SGD performs frequent updates with a high variance that cause the objective function to fluctuate heavily
- While batch gradient descent converges to the minimum of the basin the parameters are placed in, SGD's fluctuation, on the one hand, enables it to jump to new and potentially better local minima. On the other hand, this ultimately complicates convergence to the exact minimum, as SGD will keep overshooting.

Any Questions?