Age and Gender Classification using CNN

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Problem Statement

- Goal: Classify the age and gender of the faces in an image.

- Possible Applications:

    - Automated translation or Speech Generation
    - Social media websites -> use this information -> better infer the context of the image
    - Image Captioning
- Challenges: Nature of the data
  Datasets with age and/or gender labels -> smaller in size

Related Work

- Y. H. Kwon et al., Age classification from facial images [1994]
  - Early attempt for age estimation
  - Based on calculating ratios between different measurements of facial features

- S. E. Choi et al., Age estimation using a hierarchical classifier based on global and local facial features [2011]
  - Gabor and local binary patterns (LBP) + hierarchical age classifier composed of Support Vector Machines (SVM)

- B. Moghaddam et al., Learning gender with support faces [2002]
  - Applied SVM directly to image intensities.

- Most of the papers: Tackle either age **or** gender classification on constrained images.

- Gil Levi et al., **Age and Gender Classification using Convolutional Neural Networks** [2015]

  - Developed one methodology and architecture for both

  - Addresses undeniable reality: Images taken in real-world settings -> not perfectly aligned, lit, or centered

Data Set

A	B	C	D	E	F	G	H	I	J	K	L
user_id	original_image	face_id	age	gender	x	y	dx	dy	tilt_ang	fiducial_yaw_angle	fiducial_score
30601258@N03	10399646885_67c7d20df9_o.jpg	1	(25, 32)	f	0	414	1086	1383	-115	30	17
30601258@N03	10424815813_e94629b1ec_o.jpg	2	(25, 32)	m	301	105	640	641	0	0	94
30601258@N03	10437979845_5985be4b26_o.jpg	1	(25, 32)	f	2395	876	771	771	175	-30	74
30601258@N03	10437979845_5985be4b26_o.jpg	3	(25, 32)	m	752	1255	484	485	180	0	47
30601258@N03	11816644924_075c3d8d59_o.jpg	2	(25, 32)	m	175	80	769	768	-75	0	34
30601258@N03	11562582716_dbc2eb8002_o.jpg	1	(25, 32)	f	0	422	1332	1498	-100	15	54
30601258@N03	10424595844_1009c687e4_o.jpg	4	(38, 43)	f	1912	905	1224	1224	155	0	64
30601258@N03	9506931745_796300ca4a_o.jpg	5	(25, 32)	f	1069	581	1575	1575	0	30	131
30601258@N03	10190308156_5c748ab2da_o.jpg	5	(25, 32)	f	474	1893	485	484	-115	30	55
30601258@N03	10190308156_5c748ab2da_o.jpg	2	(25, 32)	m	1013	1039	453	452	-75	0	59
30601258@N03	11624488765_9db0b93c94_o.jpg	2	(25, 32)	m	101	56	740	740	-90	0	75
30601258@N03	10204739113_0e2ae11708_o.jpg	6	(25, 32)	m	336	640	841	842	-85	0	94
30601258@N03	10204739113_0e2ae11708_o.jpg	1	(25, 32)	f	693	247	720	720	-85	30	132
30601258@N03	11518638385_cac7193c86_o.jpg	2	(25, 32)	m	87	20	728	728	-95	0	79
30601258@N03	11341941104_2bcd4b99e0_o.jpg	1	(25, 32)	f	1039	1432	624	625	185	30	120
30601258@N03	11431644464_5510e0b7e9_o.jpg	2	(25, 32)	m	223	58	780	781	-85	0	40
30601258@N03	11562657036_5fe2235bed_o.jpg	5	(25, 32)	f	518	234	444	444	-15	0	78
30601258@N03	11438175534_c13ee0375c_o.jpg	2	(25, 32)	m	890	229	746	746	-105	30	132

- Specifications:

  Adience Data Set: Benchmark of face photos from flickr

  Total #photos: 26,580 Total #subjects: 2,284

  #Gender groups/labels: 2 #Age groups/labels: 8

  (0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60+)

- 5 subject-exclusive folds
- Regular Folds or Frontal Faces (fiducial_yaw_angle ~= 0)

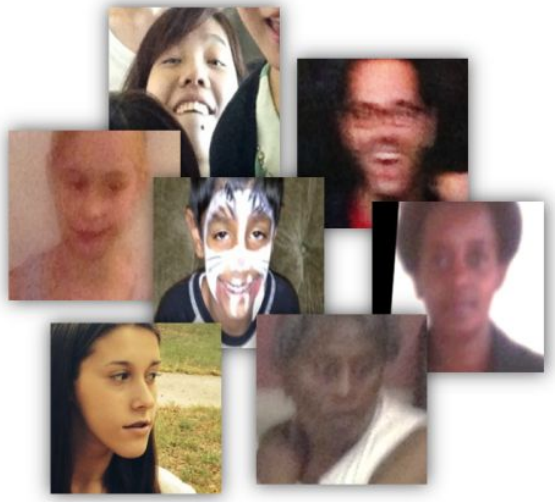
Network

Reference: Ari Ekmekji, Convolutional Neural Networks for Age and Gender Classification. http://cs231n.stanford.edu/reports2016/003_Report.pdf

- Implemented a relatively shallow architecture
- Real-world social images + Genders + Age: Limited data size
  Overfitting!
- Deeper Networks = More expressive, Better performance
  But problems can worsen due to huge numbers of model parameters

- Data Set Issues:
  - Non-Uniform Labelling:
    - Not all the images have labels for both gender and age
    - Some images have just a single number eg. 23, 14, 57
    - Some images have vague age ranges eg. (8, 23)
  - Blurred Images
  - Age distribution is skewed towards younger users
  - Inconsistent intervals in the age ranges

    (0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60+)



Reference:
http://www.openu.ac.il/home/hassner/projects/cnn_agegender/

Approach

- Primary goal: Improve performance!
- Separate the tasks of classifying men's and women's age
- Frees from having to learn a gender-neutral concept of age
- Train a chained gender-age network
- Gender Classification **easier** than Age Classification:
  - fewer number of classes
  - more marked differences exists between genders than between many age groups

- Improving the existing architecture:
  - Tested various hyperparameters for Adam Optimizer
  - Replaced the fully connected layers
  - Attempted 5 different combinations of these modified architectures.

  But no clear benefit :(

  Made the system perform the same or, sometimes, worse.

- Coupling the architectures for gender and age classification

  Step #1: classify gender

  Step #2: based on the results feed the image into an age classifier trained solely on men or solely on women.

- Observations:
  - Training a classifier only on male images = Increases accuracy when predicting the age of men

  - Accuracy of classifying female ages decreased over the average

(which may or may not be taken as a social commentary on how women are more effective at hiding their age :p)

Data Preprocessing

- Extracted images: Total# 17523
- Mostly frontal images: -45 <= fiducial_yaw_angle <= 45.
- Resized images: 227 x 227
- Center cropped
- Randomly flipped

Observations of existing model

Reference: Ari Ekmekji, Convolutional Neural Networks for Age and Gender Classification. http://cs231n.stanford.edu/reports2016/003_Report.pdf

- Reproduce the results of [1]
  - SGD + learning rate of 1e-3, decays by a factor of 10 every 10000 iterations
  - Batch size: 50 images

	Gender	Age
Benchmark [1]	85.9	45.9
Observed results	85.89	43.5

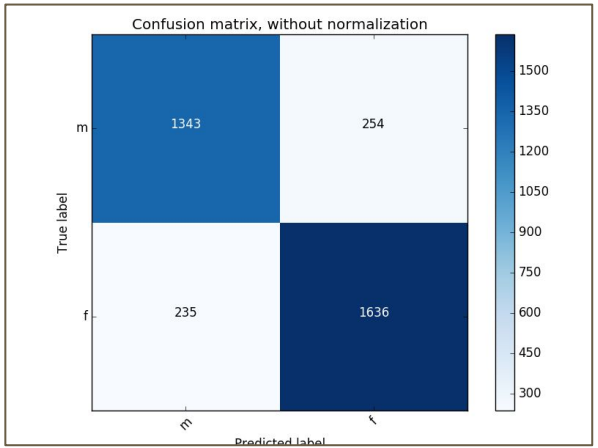
Gender Classification

Step #1

- Used the same network to classify gender
- 4 - fold cross - validation
- Train + Validation: Folds #0 - #3
- Test: Fold #4

Accuracy: 85.89%

Fold	#Males	#Females	Total
0	2047	1949	3996
1	1611	1999	3610
2	1363	1764	3127
3	1502	1820	3322
4	1597	1871	3373
	8120	9403	17523



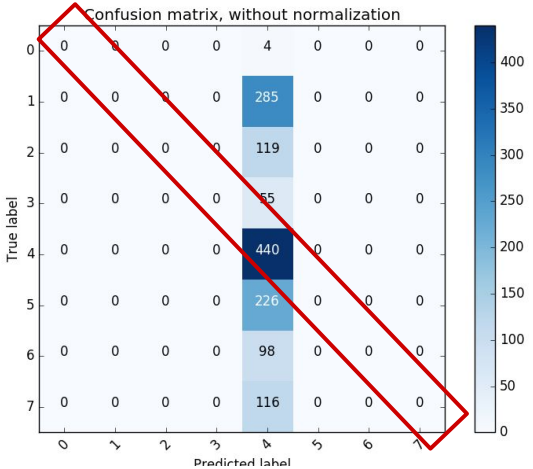
Age Classification

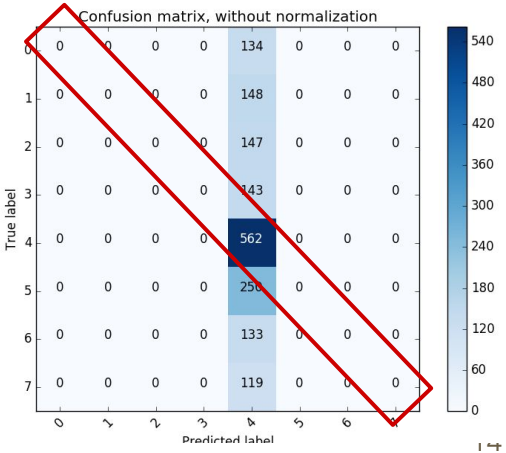
Step #2

- Used the same network to train a gender-neutral age classifier
- Tested the network based on predicted genders from Step #1
- Train + Validation: Folds #0 - #3
- Test: Data set based on predicted genders

Embarrassing...

Model #1: Same Model as it is trained for age classification	Exact Match		One - Off	
Males Total: 1343	440	32.76%	721	53.68%
Females Total: 1636	562	34.35%	955	58.37%
2979	1002	33.63%	1676	56.26%

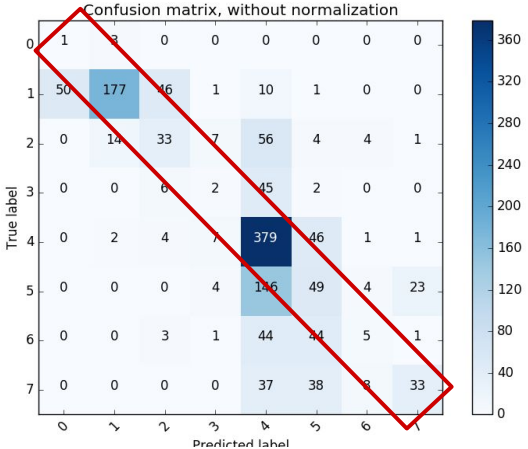


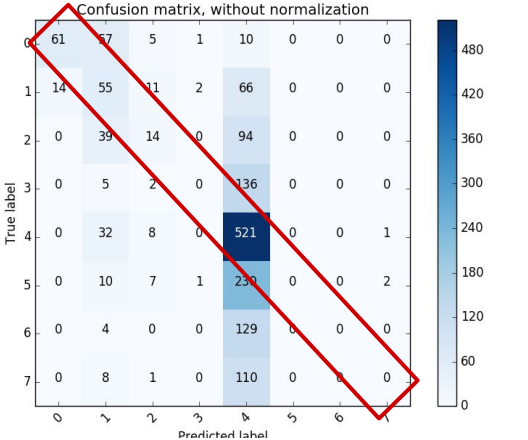


Modifications to Age Classifier

- Trained a new network solely on males and females respectively
- Weighted Losses
- Modified Dropouts

Model #2	Exact Match		One - Off	
Males Total: 1343	679	50.55%	1106	82.35%
Females Total: 1636	651	39.79%	1140	69.68%
2979	1330	44.64%	2246	75.39%





Issues

No. of males to train on: 6523

#Males	0	1	2	3	4	5	6	7
0	287	180	60	41	929	337	144	69
1	2	93	265	387	343	520	41	128
2	364	224	74	74	229	159	41	128
3	72	35	367	203	413	306	57	49

No. of females to train on: 7532

#Females	0	1	2	3	4	5	6	7
0	254	313	156	112	743	219	83	69
1	0	387	497	318	407	240	72	78
2	236	134	401	212	499	120	88	74
3	4	203	130	314	819	221	60	69

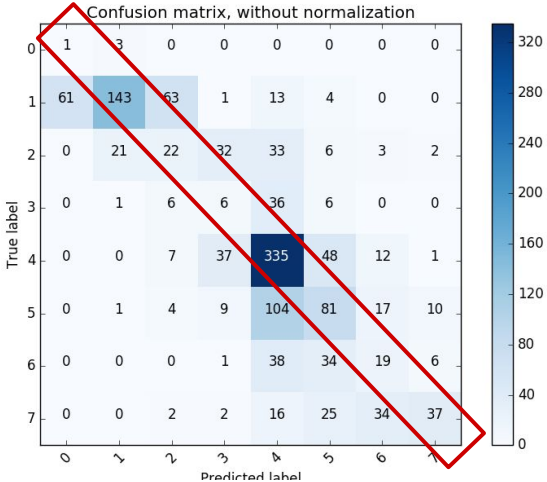
Age distribution is skewed towards younger users: Bias towards majority labels

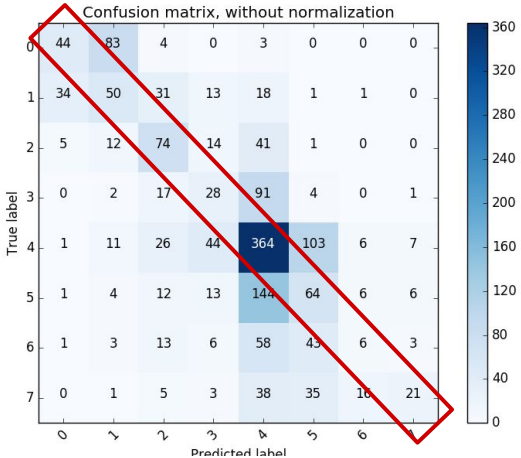
Balanced out the the dataset, but still age group #4 had more no. of images

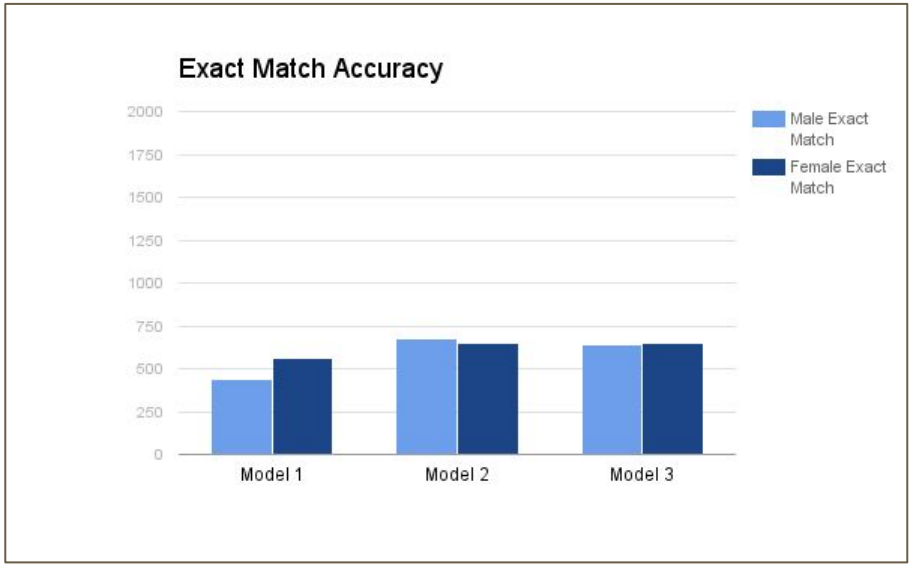
Added weighted loss(similar to previous model)

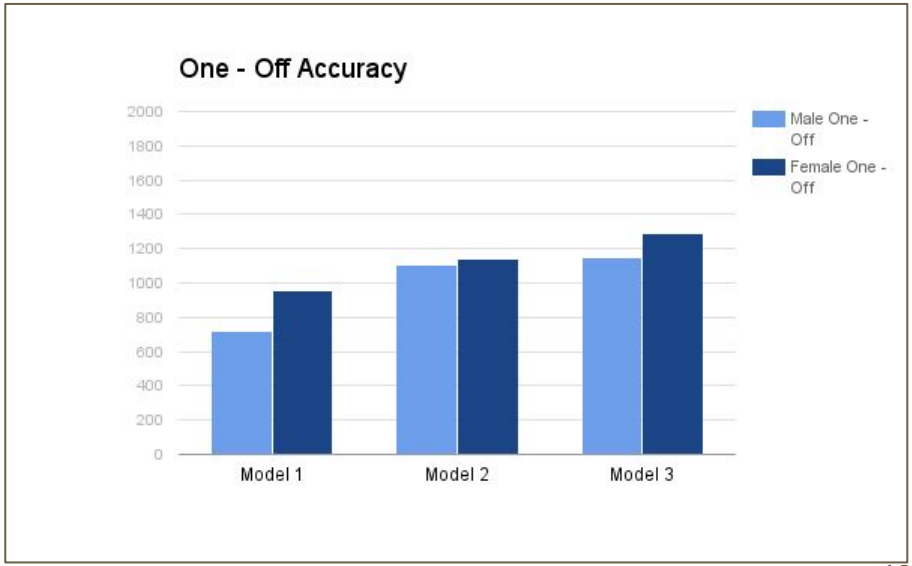
Results of Final Classifier

Model #3	Exact Match		One - Off	
Males Total: 1343	644	47.95%	1146	85.33%
Females Total: 1636	651	39.79%	1292	78.97%
2979	1295	43.47%	2438	81.83%






Exact Match Accuracy
2000
1750
1500
1250
1000
750
500
250
0
Model 1
Model 2
Model 3
Male Exact Match
Female Exact Match


One - Off Accuracy
2000
1800
1600
1400
1200
1000
800
600
400
200
0
Model 1
Model 2
Model 3
Male One - Off
Female One - Off

Future Work

- Upsample/Augment Data
- Current network can classify images with only 1 face in it. Detect faces in an image and feed the extracted faces based on the bounding boxes.
- IMDB-WIKI – 500k+ face images with age and gender labels

References

1. Gil Levi et al., Age and Gender Classification using Convolutional Neural Networks [2015]
2. Ari Ekmekji, Convolutional Neural Networks for Age and Gender Classification Stanford
3. Rajeev Ranjan et al., Unconstrained Age Estimation with Deep Convolutional Neural Networks [2015]
4. https://gist.github.com/GilLevi/c9e99062283c719c03de
5. http://www.openu.ac.il/home/hassner/projects/cnn_agegender/
6. https://github.com/Russell91/TensorBox