

PREDICTING A POLITICIAN'S PARTY AFFILIATION FROM A PHOTO



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How good are you at judging a politician by his/her cover?



☐ DEMOCRAT ☐ REPUBLICAN



☐ DEMOCRAT ☐ REPUBLICAN



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☐ DEMOCRAT ☐ REPUBLICAN



☐ DEMOCRAT ☐ REPUBLICAN

[CHECK ANSWERS](#)

diegoolano.com/demorepu/

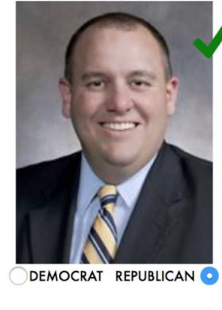
GUESS REPUBLICAN OR DEMOCRAT

ANITA JUDD-JENKINS (REPUBLICAN - KS)



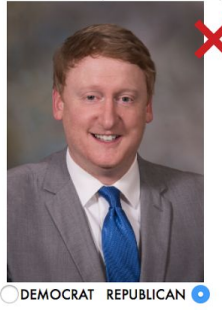
☒ DEMOCRAT ☐ REPUBLICAN

SCOTT GUNDERSON (REPUBLICAN - WI)



☐ DEMOCRAT ☒ REPUBLICAN

SYLVIA B LARSEN (DEMOCRAT - NH)



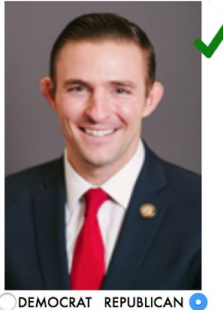
☐ DEMOCRAT ☒ REPUBLICAN

GREG BURDWOOD (DEMOCRAT - NH)



☐ DEMOCRAT ☒ REPUBLICAN

DAVID CLARK (REPUBLICAN - GA)



☐ DEMOCRAT ☒ REPUBLICAN

JOHN CHARLES EDWARDS (DEMOCRAT - AR)



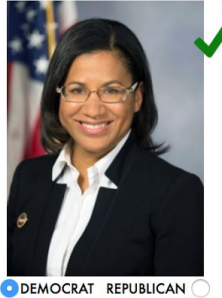
☐ DEMOCRAT ☒ REPUBLICAN

BRUCE CHANDLER (REPUBLICAN - WA)



☐ DEMOCRAT ☒ REPUBLICAN

BULLOCK, DONNA (DEMOCRAT - PA)



☒ DEMOCRAT ☐ REPUBLICAN

YOUNG, PAT (DEMOCRAT - MD)



☐ DEMOCRAT ☒ REPUBLICAN

VINCENT J. PIERRE (DEMOCRAT - LA)



☒ DEMOCRAT ☐ REPUBLICAN

CHECK ANSWERS

SCORE: 5/10

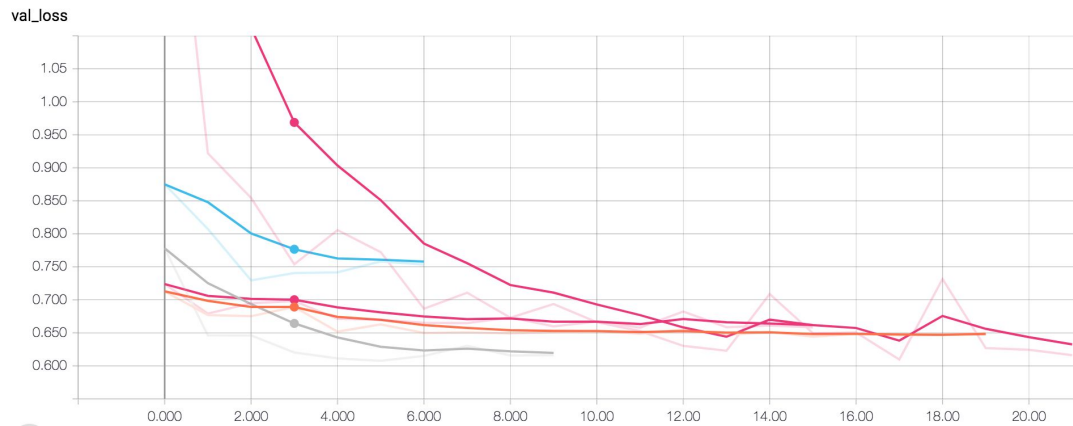
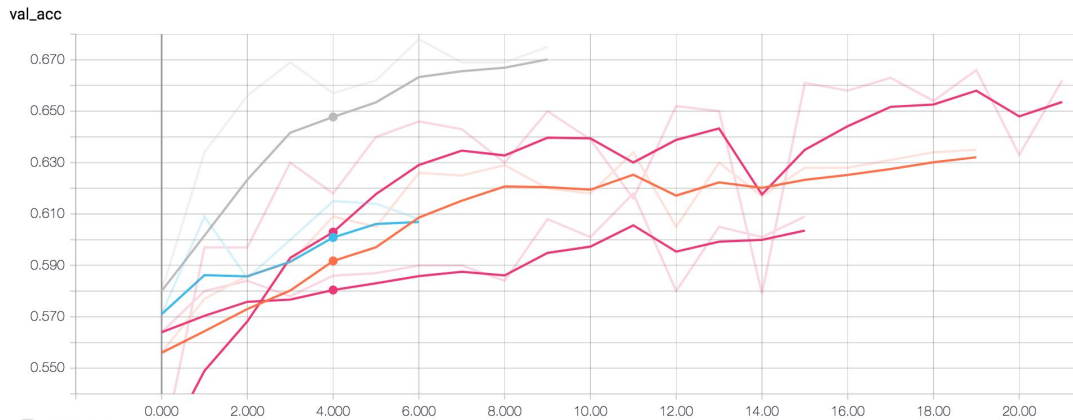
PLAY AGAIN?

after 5000 responses, the average = 65%

Dataset: color images for **11,000 US State Level** congress people
along with their name, state, and party affiliation

Models:

- VGG19, VGG16, inceptionV3, Xception, ResNet, Inception-ResNetV2 (**ImageNet**)
- VGG-Face (**Deep Face data set**) 2.6 million face images.



model	learning rate	test accuracy
inceptionv3	0.0009	0.692
resnet	0.0001	0.691
vgg19	0.001	0.670
vggFace	0.00009	0.677
xception	0.0009	0.657

models	test acc	repub acc	dem acc
inv3,res	0.697	0.791	0.582
inv3,res,v19	0.707	0.791	0.605
inv3,res,v19,xcpt	<u>0.721</u>	<u>0.784</u>	<u>0.641</u>
inv3,res,v19,xcpt,vface	0.722	0.798	0.629



Final Ensemble Model 72%

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Final Ensemble Model 72%

DEMOCRATs with high probability



REPUBLICANs with high probability



INCORRECTLY PREDICTED AS DEMOCRAT



INCORRECTLY PREDICTED AS REPUBLICAN



OBJECT DETECTION with YOLOv2, YOLO9000 , and ResNet

OBJECT DETECTION with **YOLOv2**, YOLO9000 , and ResNet

COCO Dataset (less than 100 labels)



OBJECT DETECTION with **YOLOv2**, YOLO9000 , and ResNet

COCO Dataset (less than 100 labels)



OBJECT DETECTION with **YOLOv2**, YOLO9000 , and ResNet

COCO Dataset (less than 100 labels)



label	all	republican	democrat
tie	7646 (71.6%)	4618 (<u>78.3%</u>)	3028 (<u>63.4%</u>)
person	10641 (99.7%)	5884 (99.7%)	4757(99.6%)

OBJECT DETECTION with YOLOv2, **YOLO9000**, and ResNet

9000 labels in dataset

YOLO9000 - mostly noisy (ie low probability) labels and high probability labels were of little interest "**whole**", "**neckwear**" followed by "object", "instrument", "worker", and "commodity"

OBJECT DETECTION with YOLOv2, YOLO9000 , and **ResNet**

1000 labels in ImageNet

ResNet - requires very low probability cut off to get varied results

some labels are **always wrong** no matter their probability,
"bulletproof vest", "military uniform", "oboe", "wig", "bassoon" always in **top 15 detected objects**

98% bulletproof



96% military unif



OBJECT DETECTION with YOLOv2, YOLO9000 , and **ResNet**

1000 labels in ImageNet

ResNet - requires very low to prob cut off to get varied results

almost **always correct** even if their probability is very low,

"cowboy hat", "flagpole", "bolo-tie", "bow tie", and "windsor tie", (cowboy hat / flag pole very rare)
21 / 61 out of 32,000

5% cowboy hat



7% flagpole



OBJECT DETECTION with YOLOv2, YOLO9000 , and **ResNet**

1000 labels in ImageNet

ResNet - why manual verification is needed



OBJECT DETECTION with YOLOv2, YOLO9000 , and **ResNet**

1000 labels in ImageNet

ResNet - why manual verification is needed



Neck Brace (96%)



Chainmail (99%)



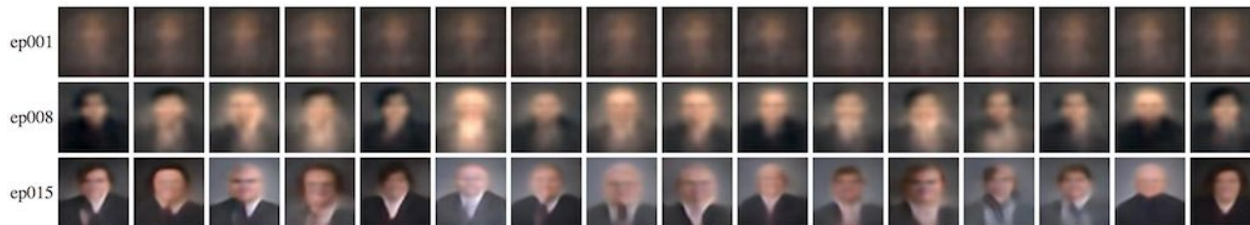
Boa Constrictor (30 %)

Boundary Equilibrium Generative Adversarial Networks (beGAN)

Fake “new” politicians

Boundary Equilibrium Generative Adversarial Networks (beGAN)

All Politicians
(64 x 64)



Boundary Equilibrium Generative Adversarial Networks (beGAN)

All Politicians
(64 x 64)



“male whitening”

Boundary Equilibrium Generative Adversarial Networks (beGAN)

All Politicians verification
(via Nearest Neighbors)

CLOSEST IMAGE TO



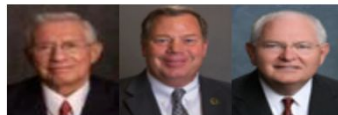
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CLOSEST IMAGE TO



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CLOSEST IMAGE TO



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CLOSEST IMAGE TO



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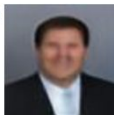
CLOSEST IMAGE TO



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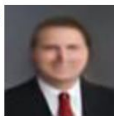
CLOSEST IMAGE TO



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CLOSEST IMAGE TO



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Boundary Equilibrium Generative Adversarial Networks (beGAN)

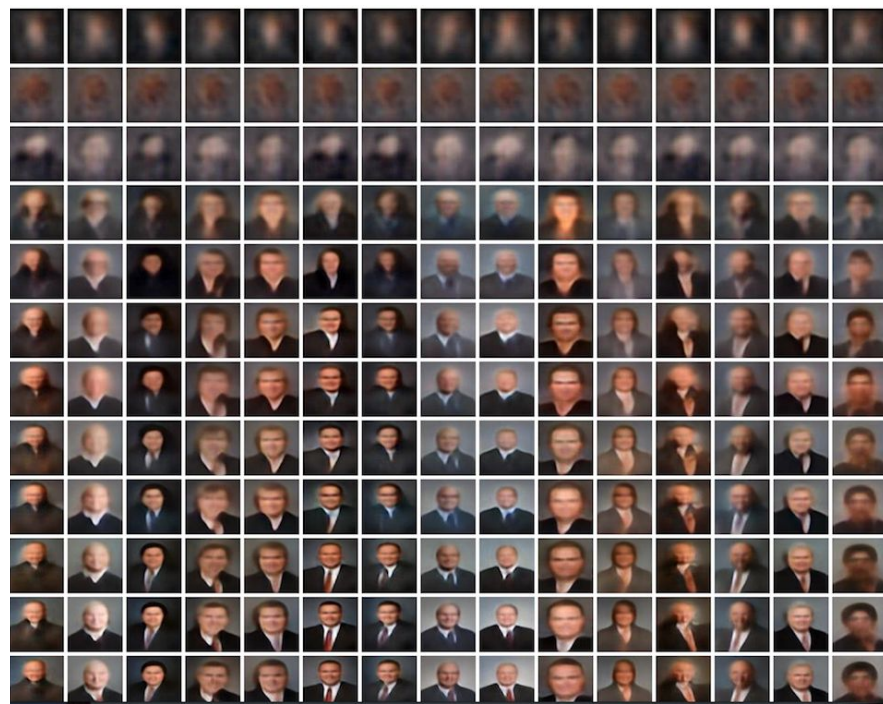
All Politicians (64 x 64)



Republicans (64 x 64)



Democrats (64 x 64)



All politicians (128 x 128) = 4 days training vs 1 day for prior GANs



Conclusions:

- 1) Constructed 11 thousand color images data set of politicians with meta data
- 2) Gathered 5000 human responses to establish baseline of 65%
- 3) Final model with 72% accuracy for predicting party affiliation from image alone



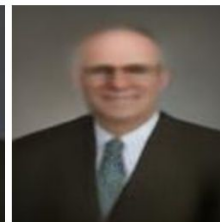
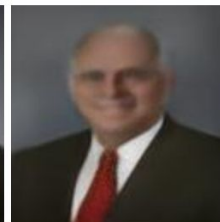
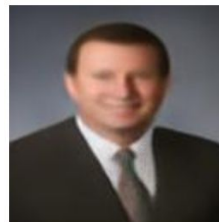
party?
state?



party?
state?



- 4) Use of object detection systems to better understand test results
- 5) Use of GANs to generate new politicians



THANKS !