

# PREDICTING A POLITICIAN'S PARTY AFFILIATION FROM A PHOTO



Diego Garcia-Olano, Amin Anvari, Farzan Memarian

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



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN



DEMOCRAT  REPUBLICAN

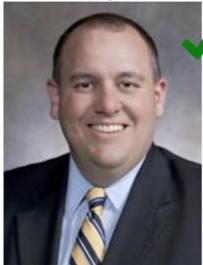
[CHECK ANSWERS](#)

## 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

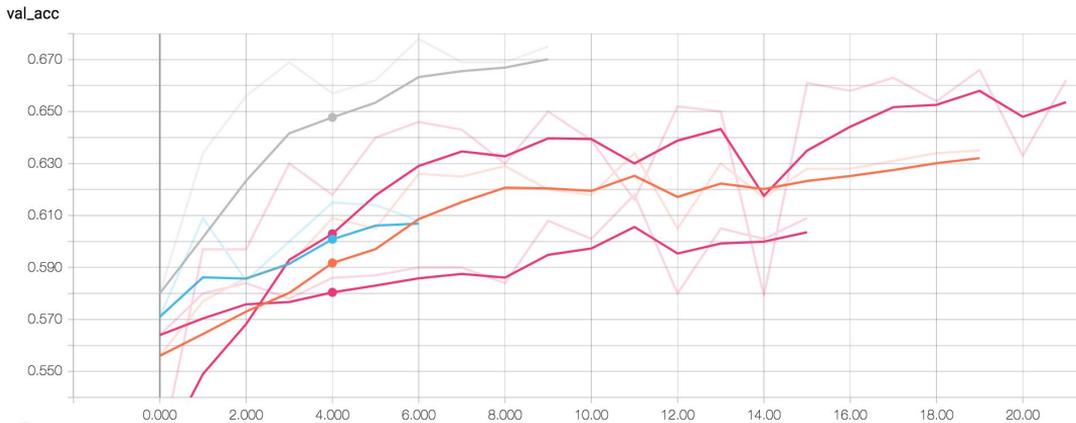
PLAY AGAIN?

after 5000 responses, the average = 65%

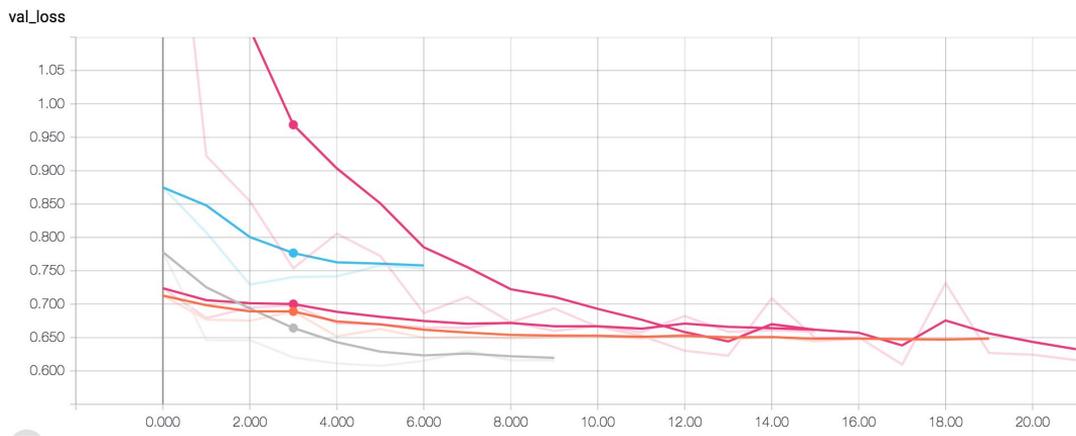
Dataset: color images for **11,000 US State Level** congress people  
along with their name, state, and party affiliation

Models:

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



<u>model</u>	<u>learning rate</u>	<u>test accuracy</u>
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



<u>models</u>	<u>test acc</u>	<u>repub acc</u>	<u>dem acc</u>
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%

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%

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		:	
CLOSEST IMAGE TO		:	
CLOSEST IMAGE TO		:	
CLOSEST IMAGE TO		:	
CLOSEST IMAGE TO		:	
CLOSEST IMAGE TO		:	
CLOSEST IMAGE TO		:	

# Boundary Equilibrium Generative Adversarial Networks (beGAN)

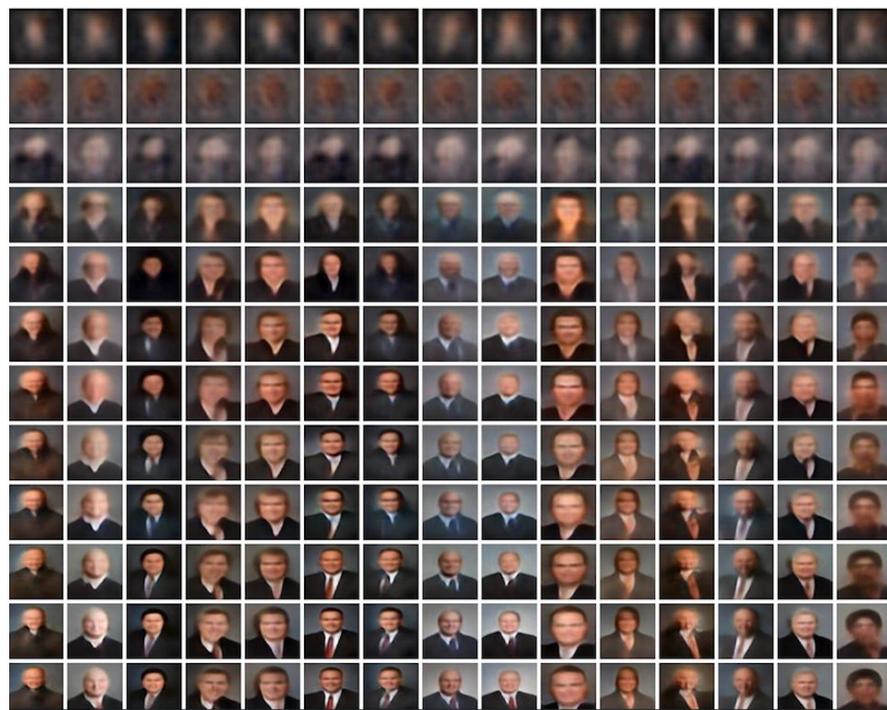
## All Politicians (64 x 64)



## 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



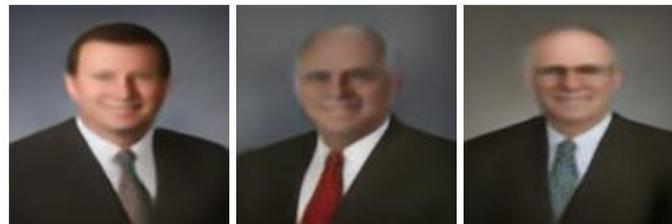
party?  
state?



party?  
state?



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



**THANKS !**