Enriching Historic Photography with Structured Data using Image Region Segmentation

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Introduction

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- Our approach: Use computer vision techniques!

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- even when labeled as automated studies have shown that people have trouble accurately interpreting probabilistic data and are overly confident in predictions (Khaw, Luminita, Woodford, 2019)
- risk reinforcing racial, gender, and socioeconomic biases inherent in the training data behind machine learning techniques

Data

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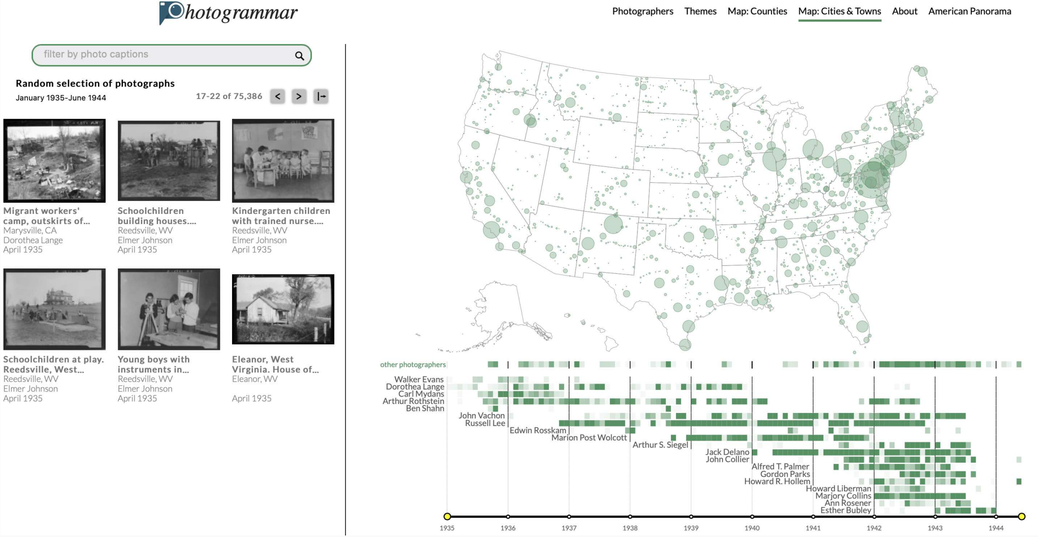
- indicative of many documentary photography collections held in GLAM institutions
- a collection we have worked with through out Photogrammar project since 2010

Photogrammar



Previous Approaches

Computer vision methods for creating structured data from still photography:

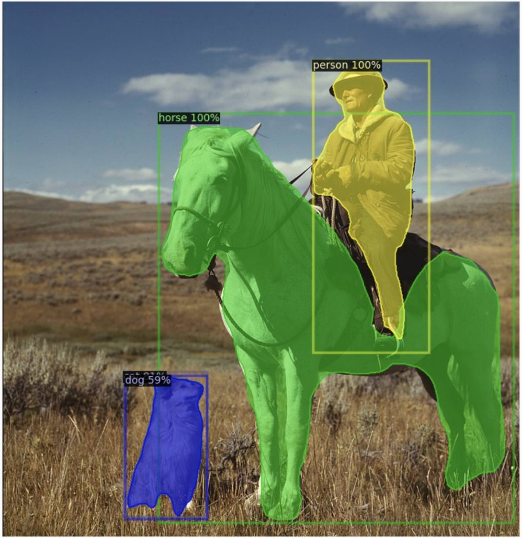
- object detection
- automatic free-form captions
- image embeddings

Object Detection

Mask R-CNN instance object classification algorithm (X101-FPN).

Wu, Y., Kirillov, A., Massa, F., Lo, W.-Y., and Girshick, R. (2019). *Detectron2.*

Object Detection



Object Detection

Object Detection

Automatic Captions

Show, attend and tell

Xu, Kelvin, et al. “Show, attend and tell: Neural image caption generation with visual attention.” *International conference on machine learning.* 2015.

Automatic Captions

a man is wearing a hat and a hat

a woman is sitting on a stage with a microphone

a man is sitting on top of a pile of oranges

a couple of giraffes are in a room

Image Embedding

VGG-19

K. Simonyan, A. Zisserman "Very Deep Convolutional Networks for Large-Scale Image Recognition." *arXiv:1409.1556*

Image Embeddings

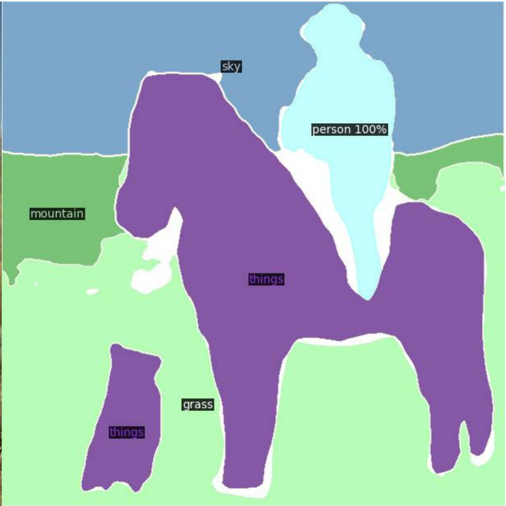
Image Segmentation

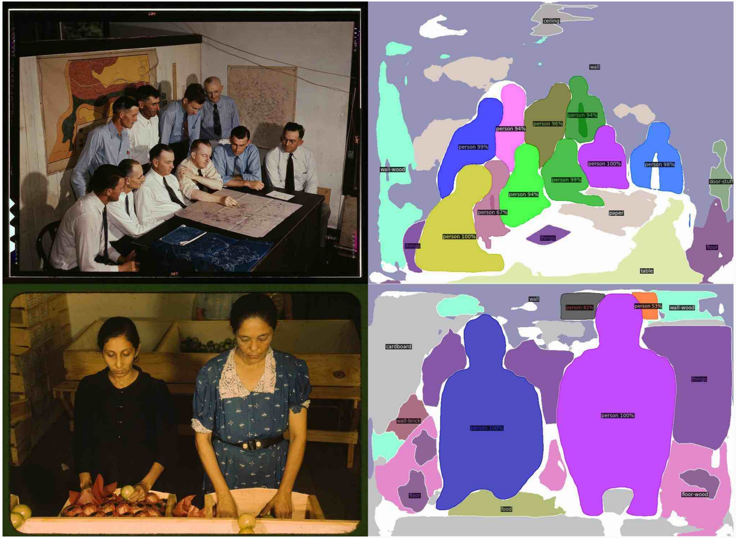
Image Embedding

COCO-stuff

Caesar, H., Uijlings, J., & Ferrari, V. (2018). "COCO-stuff: Thing and stuff classes in context." In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 1209-1218).

Group	Meta	Categories
indoor	ceiling	ceiling-tile
indoor	floor	floor-wood; floor-stone; floor-tile; floor-marble; carpet
indoor	food	fruit; vegetable; salad
indoor	furniture	cabinet; cupboard; counter; desk; door; light; mirror; shelf; stairs; table
indoor	rawmaterial	cardboard; metal; paper; plastic
indoor	textile	banner; blanket; curtain; cloth; clothes; napkin; mat; pillow; rug; towel
indoor	wall	wall-brick; wall-stone; wall-tile; wall-wood; wall-panel; wall-concrete
indoor	window	window-blind
outdoor	building	bridge; house; roof; skyscraper; tent
outdoor	ground	dirt; gravel; pavement; platform; playingfield; railroad; road; sand; snow; mud
outdoor	plant	flower; grass; tree; bush; leaves; branch; moss; straw
outdoor	sky	clouds
outdoor	solid	mountain; rock; hill; stone; wood
outdoor	structural	fence; net; railing; cage
outdoor	water	river; sea; waterdrops; fog


sky
person 100%
mountain
things
grass
things


ceiling
wall
person 94%
person 96%
person 94%
person 99%
wall-wood
person 100%
person 98%
door-stuff
person 99%
person 94%
person 67%
paper
things
person 100%
things
floor
table
wall
person 82%
person 53%
wall-wood
cardboard
things
person 100%
wall-brick
person 100%
floor
floor-wood
food

Creating Structured Data

Creating structured data

Our method:

- apply the image segementation algorithm
- record any detected ‘stuff’ region along with the percentage of the image covered
- record total percentage of ‘thing’ regions
- record number of ‘people’ regions

Web Annotation Data Model: Example I

```
<http://photogrammar.org/anno1> a oa:Annotation ;
  dcterms:creator <http://photogrammar.org/tarnold2> ;
  dcterms:created "2020-02-19T12:00:00Z" ;
  oa:hasBody [
    a                        pgram:ImageSegmentationRegion ;
    pgram:regionName         <http://example.org/stuff/things> ;
    pgram:regionPercent      32 ;
  ] ;
  oa:hasTarget <http://photogrammar.org/resource/1a35022v> ;
  oa:motivatedBy oa:tagging .
```

Web Annotation Data Model: Example II

```
<http://photogrammar.org/anno2> a oa:Annotation ;
  dcterms:creator <http://photogrammar.org/tarnold2> ;
  dcterms:created "2020-02-19T12:01:00Z" ;
  oa:hasBody [
    a                        pgram:ImageSegmentationRegion ;
    pgram:regionName         <http://example.org/stuff/people> ;
    pgram:regionPercent      6 ;
    pgram:regionCount        1 ;
  ] ;
  oa:hasTarget <http://photogrammar.org/resource/1a35022v> ;
  oa:motivatedBy oa:tagging .
```


snow
bridge
wall-brick
person


sky
food
mountain
railroad

Evaluation

Quantitative evaluation

Hand labelled accuracy of the annotations generated by each method.

	Accuracy	**Images Labelled**	**Unique Results**
Captions	31.5%	100%	1040
Objects	70.7%	37.3%	178
Stuff & People	97.5%	98.9%	1140

Future Directions

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- further encode information about the detected regions ⟶ dominant colors of each region type; describe regions by quadrant
- develop a structured language for creating image captions from the structured data
- hierarchical version of a tagged object detection algorithm that simulates the stuff-based regions