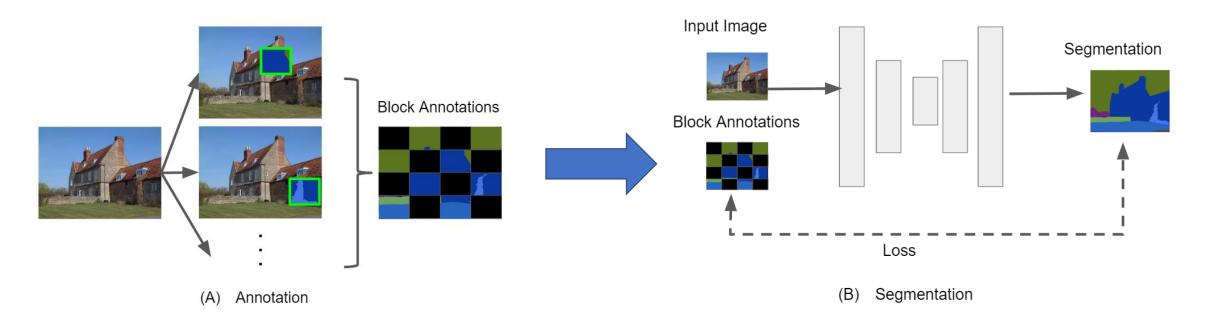
Efficient Image Annotation for Semantic Segmentation







Hubert Lin Paul Upchurch Kavita Bala

Goal: More efficient annotation for semantic segmentation.

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- Low cost
 - Low annotation time / monetary cost.
 - Depends on task difficulty and worker skill.
- High performance
 - Good training data for segmentation.
 - Depends on label quality (label completeness / label noise).

- Strong supervision: dense pixel-level labels
 - Gold standard, highest performance.
 - Expensive to collect (e.g. 90 min per images for Cityscapes).
 - Difficult task many standard datasets utilize expert workers for annotation (Cityscapes, ADE20k, Pascal Context, Mapillary Vistas...).





- Weak supervision
 - Dense pixel-level labels are expensive, so a lot of work on leveraging weak supervision for segmentation.
 - Weak supervision can be used stand-alone or in semi-supervised setting.

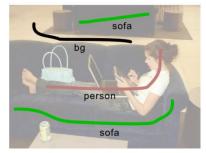




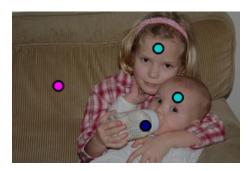
Weak supervision



Coarse Segments



Scribbles



Point Clicks



Image-level Labels



Bounding Boxes

[Cordts et al 2016; Bearman et al 2015; Lin et al 2016; Dai et al 2015]

- What about interactive segmentation for annotation?
 - Deep Extreme Cut
 - Deep Object Selection
 - Fluid Annotation
 - Interactive Full Image Segmentation by Considering All Regions Jointly
 - PolygonRNN++
 - Curve-GCN
 - ...
- Modern deep learning based approaches require seed training data.
 Manual annotation required for high quality seed training data.

Goal: More efficient annotation for semantic segmentation.

Low cost

Low Time	e / Image		High Time / Image
Point Clicks	Scribbles	 Coarse Segments	Full-Image Pixel-level

High performance

Low Perfor	mance		High Performance
Point Clicks	Scribbles	 Coarse Segments	Full-Image Pixel-level

Goal: More efficient annotation for semantic segmentation.

Low cost

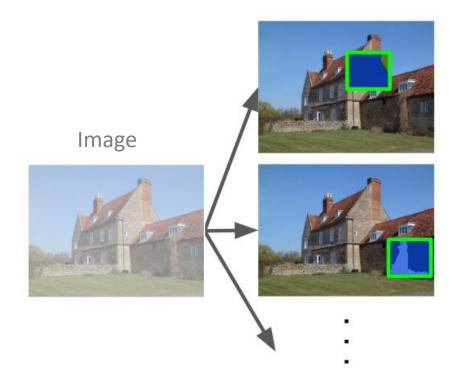
Low Time / ImageHigh Time / ImagePoint ClicksScribbles ... SegmentsFull-Image Pixel-level

High performance

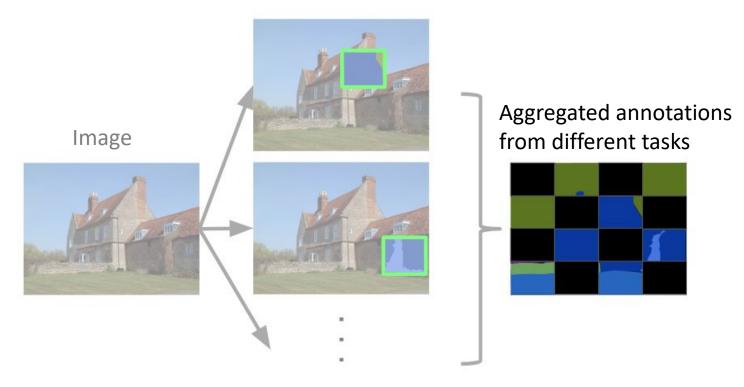
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Image

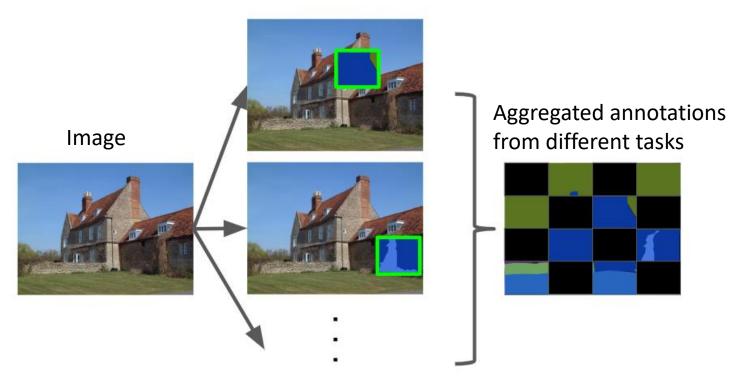




Pixel-level annotations in small blocks

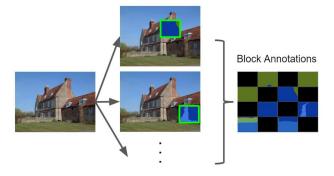


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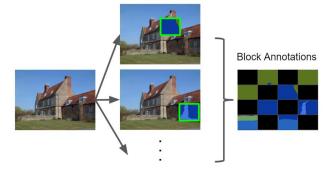


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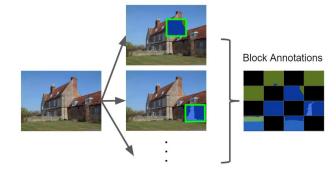
• At first glance, this approach has several appealing properties:



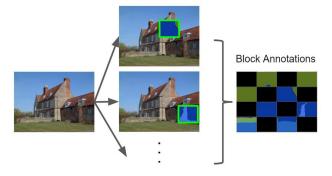
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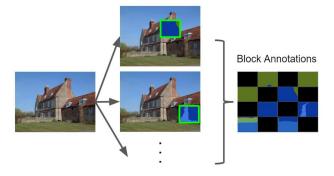
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 - Small image region is equivalent to a small image.
 - Tools and required skillsets are familiar to crowdworkers.
 - Negligible engineering required to deploy in practice.



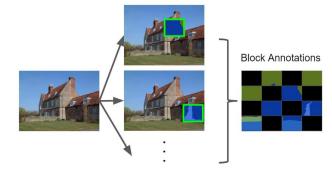
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 - Low difficulty.



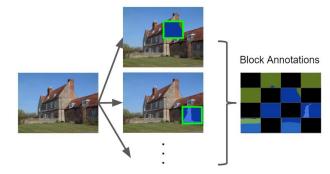
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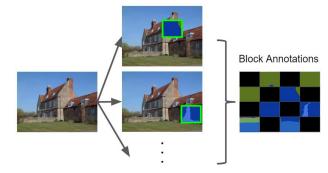
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 - Pixel-level labels within annotated regions, in contrast to other forms of weak supervision.
 - Useful for training semantic segmentation networks.



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- This leads to several questions...



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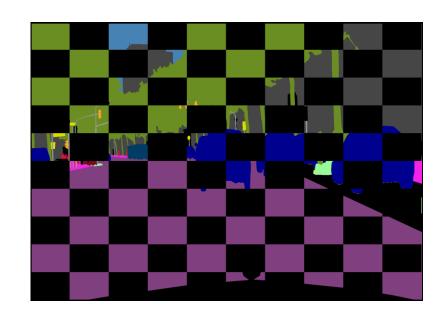
 Are these types of annotations effective for learning semantic segmentation, especially if only a small number of blocks are annotated?

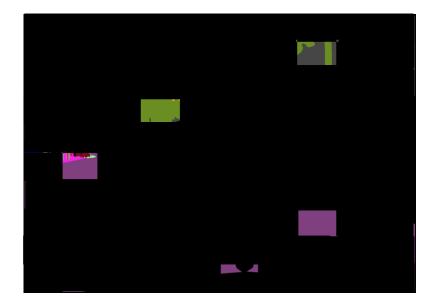
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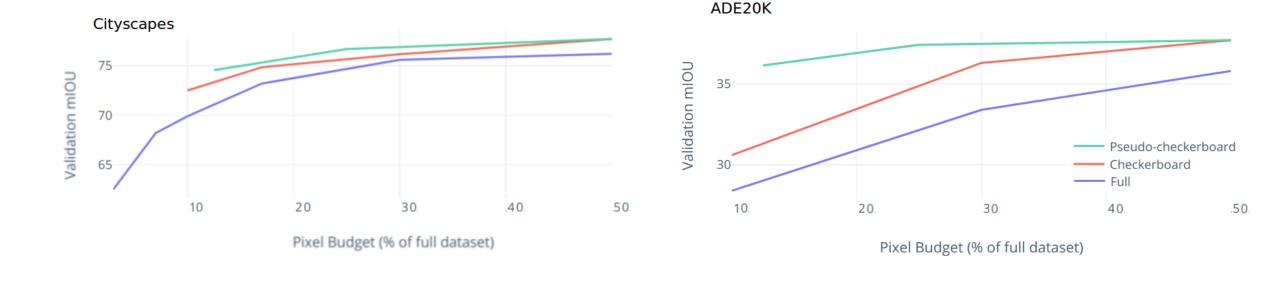
- Experimental set-up:
 - Datasets: Cityscapes, ADE20K. Chosen for variety in # classes, types of classes, environments.
 - Network: DeepLabv3+ w/ Xception backbone.
 - Block annotation: image divided into 10x10 grid; # of labeled blocks varies.





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- Block annotation outperforms full-image annotation given the same number of annotated pixels.



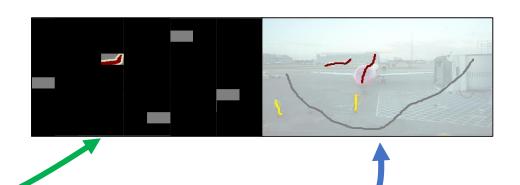
- Q: How does block annotation compare to full-image annotation?
- Block annotation achieves same performance as full-image annotation with half the pixels annotated.

	Optimal (Full)	Block-50%	Block-12%
Cityscapes ADE20K	77.7	77.7	74.6
ADE20K	37.4	37.2	36.1

• Q: How does block annotation perform against other forms of weak supervision?

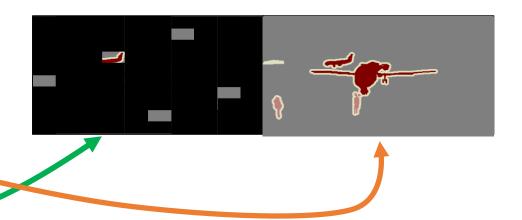
- Q: How does block annotation perform against other forms of weak supervision?
- Block annotation outperforms existing weakly-supervised methods given equivalent annotation time.

Cityggapag	Ours: Block	Coarse	Full Supervision
Cityscapes	(7 min)	(7 min [14])	(90 min [14])
mIOU (%)	72.1	68.8	77.7
Doggo 1	Ours: Block	Scribbles	Full Supervision
Pascal	Ours: Block (25 sec)	Scribbles (25 sec [36])	Full Supervision (4 min [41])
Pascal mIOU (%)			Full Supervision (4 min [41]) 69.6



- Q: How does block annotation perform against other forms of weak supervision?
- Block annotation achieves up to 97% of strong supervision with 1/10th annotation time.

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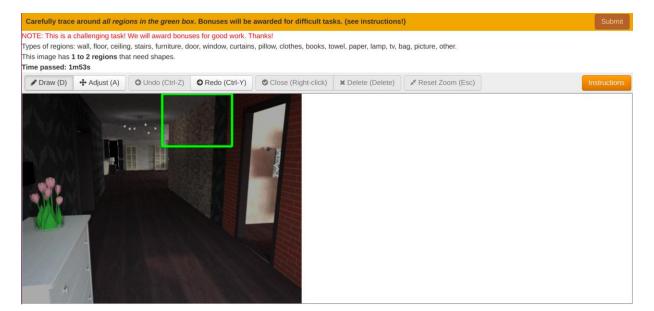


- Q: How does block annotation perform against other forms of weak supervision?
- Block annotation's performance does not depend on additional loss functions or label propagation (e.g. scribble/box methods)

Method	Annotations	mIOU (%)
MIL-FCN [46]	Image-level	25.1
WSSL [45]	Image-level	38.2
point sup. [7]	Point	46.1
ScribbleSup [36]	Point	51.6
WSSL [45]	Box	60.6
BoxSup [15]	Box	62.0
ScribbleSup [36]	Scribble	63.1
Ours: Block-1%	Pixel-level Block	61.2
Ours: Block-5%	Pixel-level Block	67.6
Ours: Block-12%	Pixel-level Block	68.4
Full Supervision	Pixel-level Image	69.6

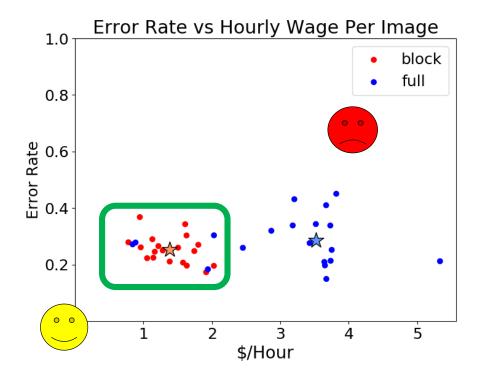
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- Experimental setup:
 - Datasets: Cityscapes (representative of 'hard' dataset); SUNCG/CGIntrinsics (synthetic, has ground truth labels).
 - Interface based on OpenSurfaces
 - User study performed on Amazon Mechanical Turk



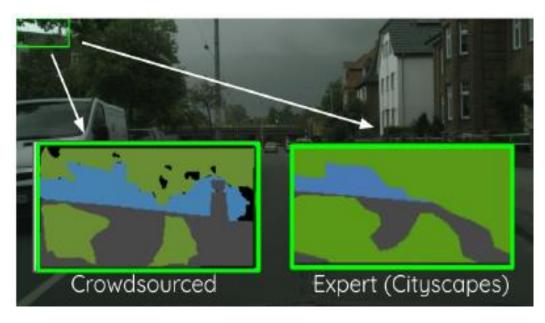
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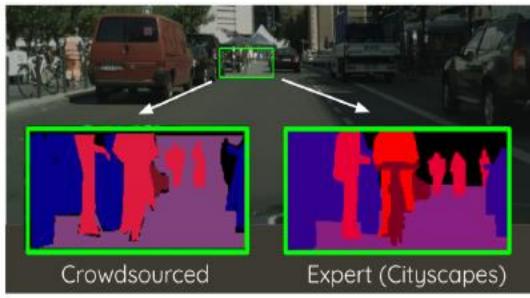
- Q: What is the cost of annotation?
- We find that workers produce quality annotations while demanding lower wage. Quality (error rate) measured vs ground truth in SUNCG.



• Q: What is the quality of annotation?

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- We find crowdworkers produce work that is qualitatively comparable to work by expert workers on Cityscapes.





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- We receive overwhelmingly positive feedback from workers across both studies on SUNCG and Cityscapes.

	"Nice" "Good" "Great"	"Fun" "Happy"	"Easy"	"Okay"	Release More HITs	Increase Pay
#	8	5	4	2	2	3

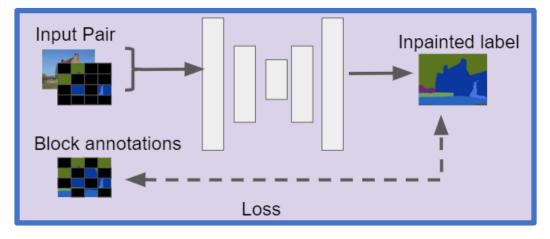
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Block Annotation

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 - What is the annotation cost / quality? How do workers respond to this task?
 - Can a partially labeled image be converted to a fully labeled image automatically?

- Experimental setup:
 - Datasets: Cityscapes, ADE20K
 - Network: DeepLabv3+ modified with input channel of labeled blocks.
 - Train by sampling annotated blocks; inference with all annotated blocks.





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(a) Full human labels



(c) Inpainted labels (all)



(b) Original image



(d) Label agreement (white)

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mIOU: 92% (vs 78% from automatic segmentation)

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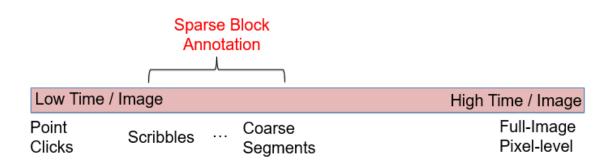
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Sparse block annotations:

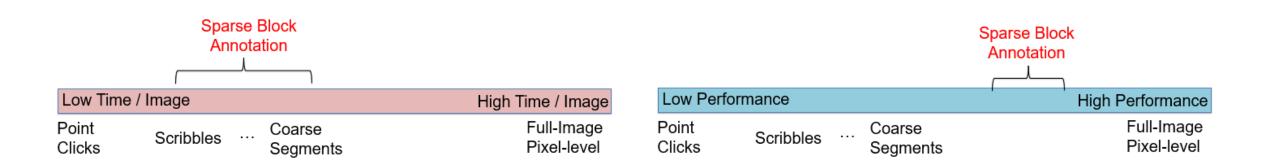
Sparse block annotations:

• are scalable, cost-effective, and easy to implement.



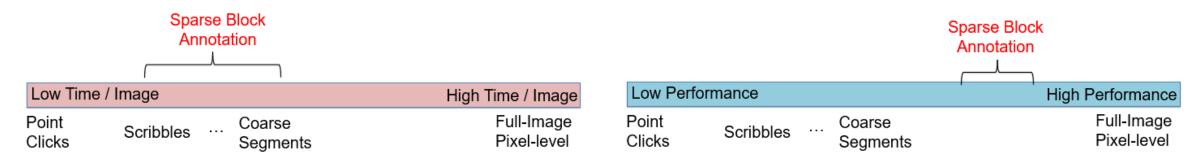
Sparse block annotations:

- are scalable, cost-effective, and easy to implement.
- enable high semantic segmentation performance in weaklysupervised settings and scales to strongly-supervised performance.

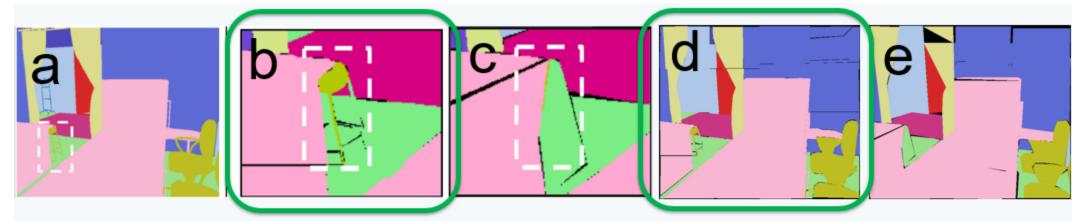


Sparse block annotations:

- are scalable, cost-effective, and easy to implement.
- enable high semantic segmentation performance in weaklysupervised settings and scales to strongly-supervised performance.
- can be converted to high quality full-image pixel-level annotations.



Thank you!



SUNCG. All segments are crowdsourced. Left to right: (a) Ground truth

- (b) Block annotation (zoomed-in) (c) Full-image annotation (zoomed-in)
- (d) Block annotation (e) Full-image annotation.

Small stool is missed by full-image annotation in this example (b vs c).

The boundaries across different block tasks line up well (d vs e).