

An active learning framework to optimize training of deep models with human-in-the-loop

Training with less labels

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Figure Eight

HOW **BIG** IS BIG DATA?



2.7 Zetabytes (that's 27 with 21 0s after it) of data exist in the digital universe today.



By 2020 analysts predict the amount of data will be 50x what it is today.



In 2012 90% of all the data that existed in our entire history had been created in the previous 2 years.

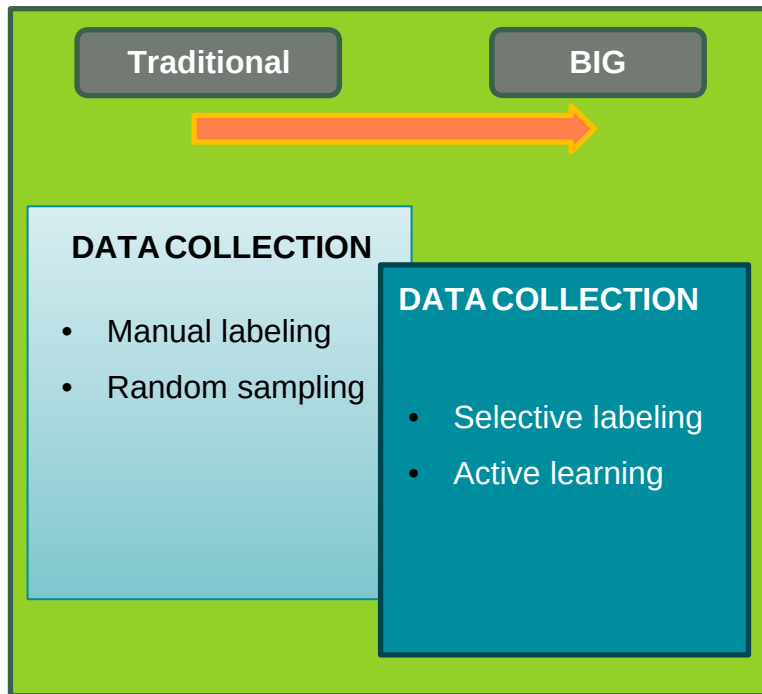


Every 2 days we create as much information as we did from the beginning of time up to 2003.

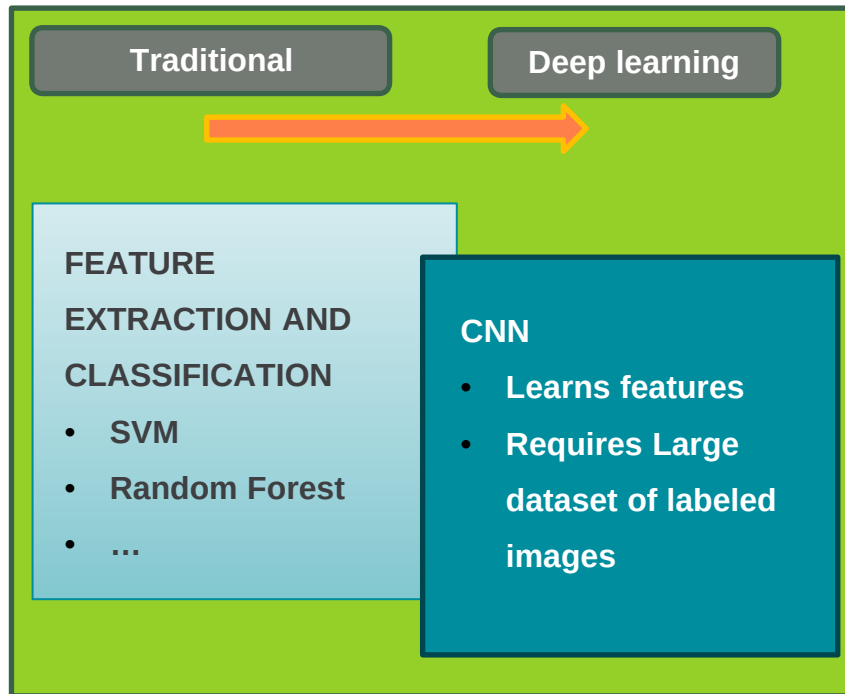
We need to find better and more efficient ways to label and use our data

Supervised Learning

Data



Predictive Modeling



Data is **abundant** but labeling is **expensive**

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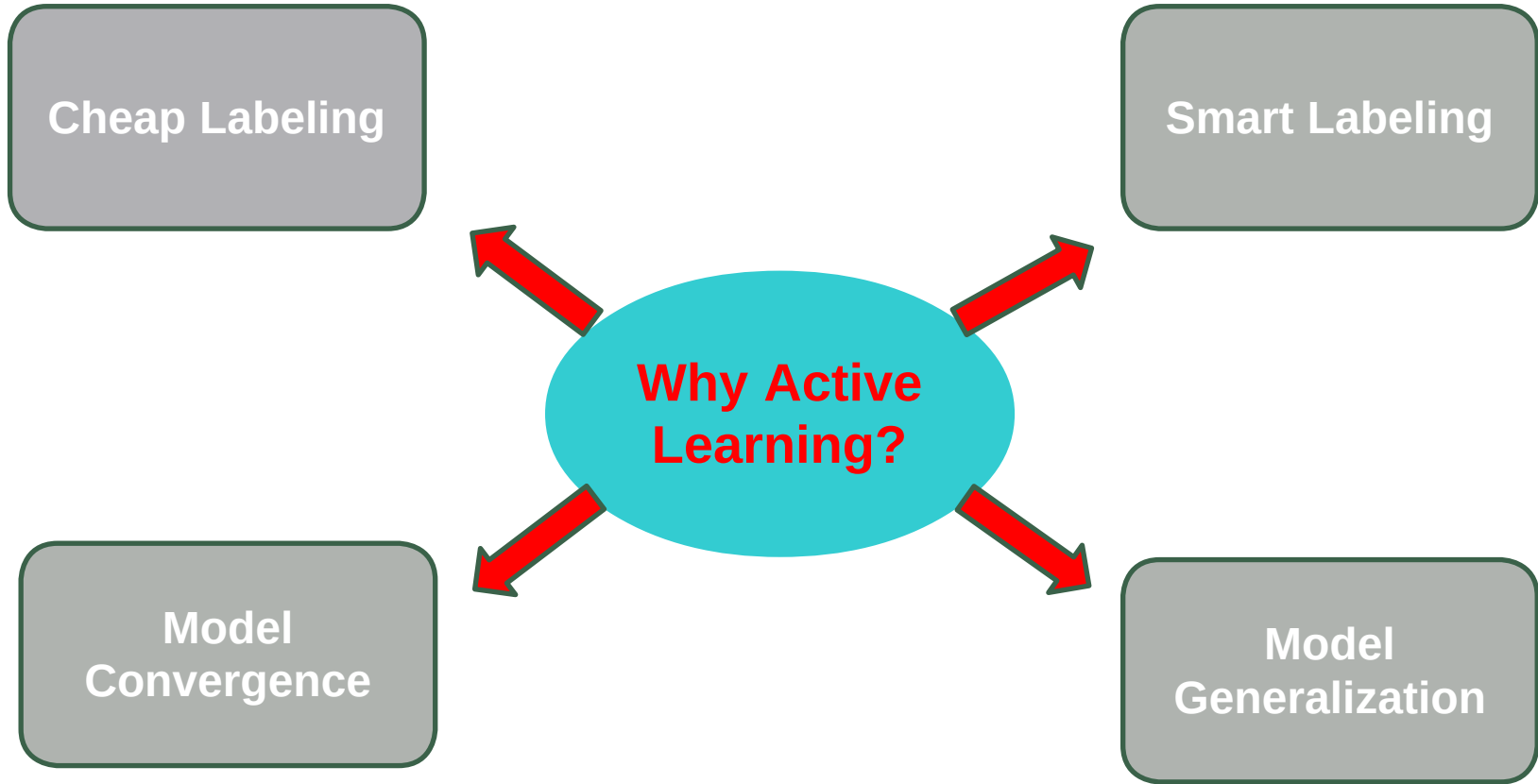
1 Pre-training: cheap large datasets on related domain



2 Fine-tuning: expensive well-labeled data



Performance
boost!



Once & for all

**Entire
Dataset
Labeling**

Before Training

Prioritizer

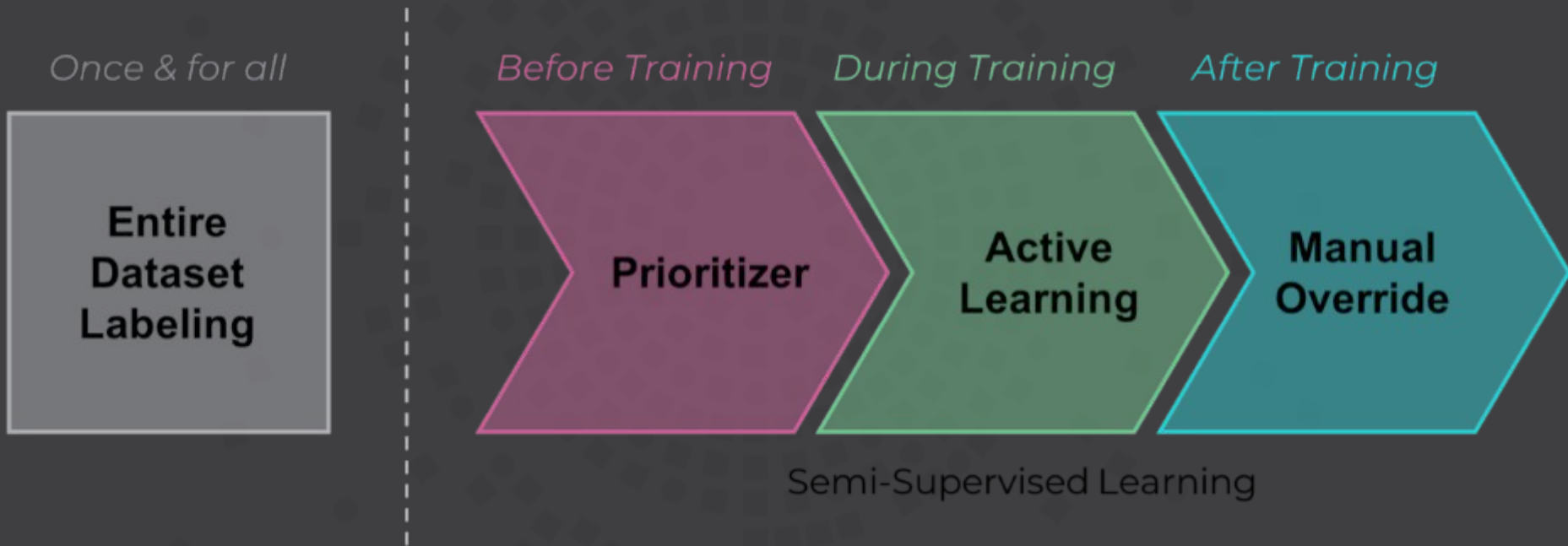
During Training

**Active
Learning**

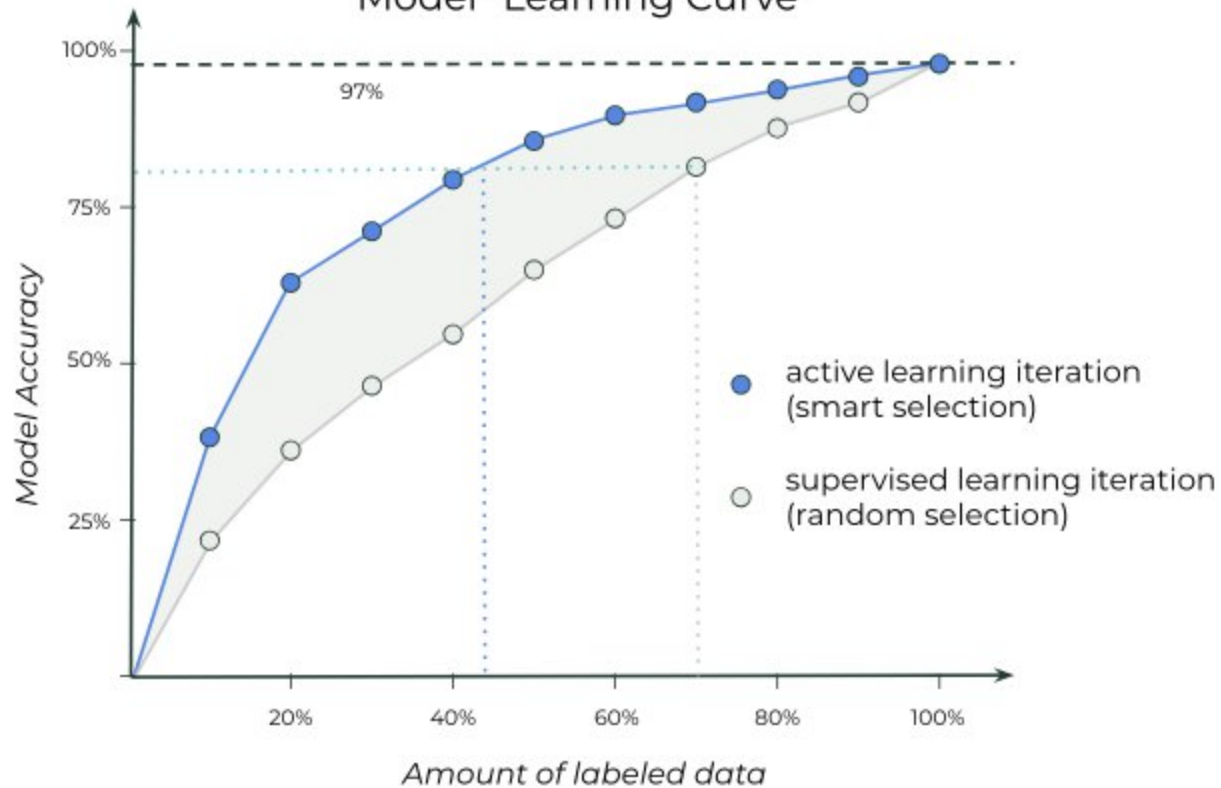
After Training

**Manual
Override**

Semi-Supervised Learning



Model "Learning Curve"





Application to Parking Sign Recognition

Active Learning Framework

Can I park here?

Drivers spend a lot of time deciphering parking rules

- Create traffic jams
- Endanger pedestrians safety
- Harm transportation environment
- High rate of parking tickets





How computer vision can help to improve parking experience and transportation experience?

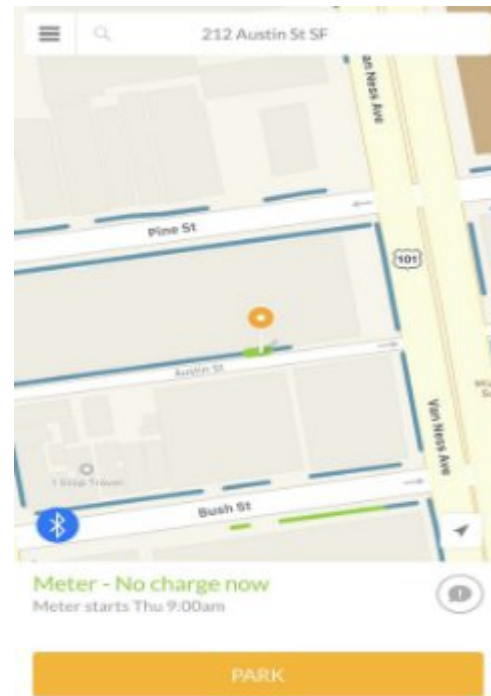
Structuring The Data

Online street-level imagery provides opportunities for developing new vision based algorithm

- Detect, classify and localize parking meters



Transferring the parking rules from images to maps





**Data collection and structuring
Is the first step to build any model**

Street-level image collection and visualization

- Google street-view, Microsoft Streetside, Mapjack, EveryScape and ...
- **Google Street-View**
 - 9 directional camera for 360 degree views at the height of 2.5 - 3 meters
 - multiple GPS units for positioning
 - 3G/GSM/Wi-Fi antennas for scanning
 - 3G/GSM and Wi-Fi hotspots



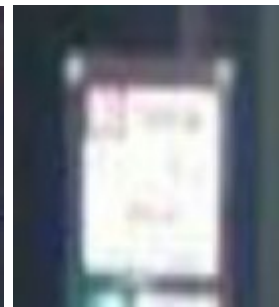
Developing computer vision models

It is a challenging task!

- **Appearance information**

- different shapes, color and dimensions
- contains a lot of text
- Inter-class and intra-class

variability



- **Standard computer vision challenges**

- varying illumination
- Pose and viewpoint
- Occlusion
- Confusion with man-made object

Making sense of a messy world



Data Collection and Annotation

**Download and split
panoramas into chips**

**Label the images for
Parking Sign**

Human

**Fine-tune the model
& Identify where model
is not performing well**

Machine

Data Collection

1. Download and Split Panoramas into Chips



Data Collection

2. Launch a Review Job to select Chips



Is there a parking sign in this image? (press enter)

☐ Yes

☒ No

19%

92%

REASON: (Choose when contributors choose the question)

There is no clear parking sign in this image. If the parking sign is too small or the text is not visible or more than half of the sign is occluded do not verify it.



Data Collection

3. Launch a Labeling Job to Box Parking Signs



Examples	
Description	Example image
1. Exclude the sign	
2. You should not label parking signs in the image if the parking sign is not visible in the image.	
3. You should not label parking signs in the image if the parking sign is not visible in the image.	
4. You should not label parking signs in the image if the parking sign is not visible in the image.	
5. You should not label parking signs in the image if the parking sign is not visible in the image.	
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20. You should not label parking signs in the image if the parking sign is not visible in the image.	

Figure Eight Image Annotation Toolbox

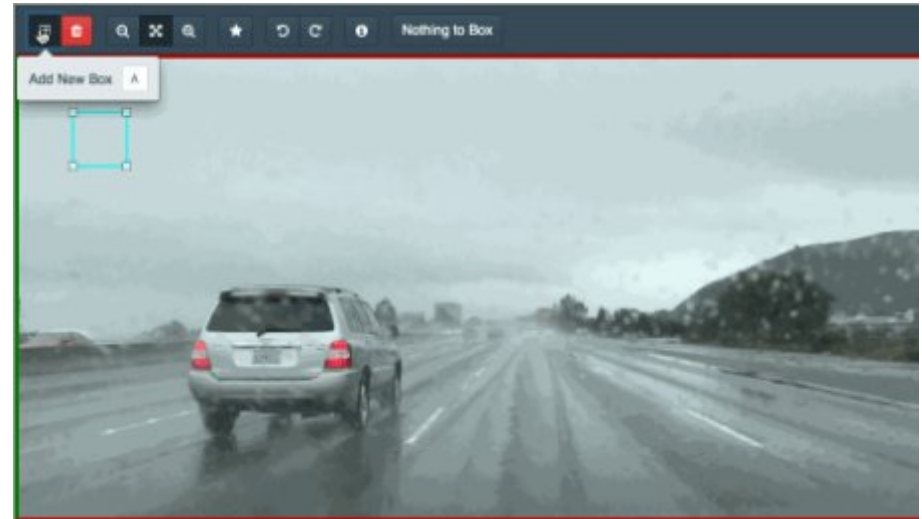


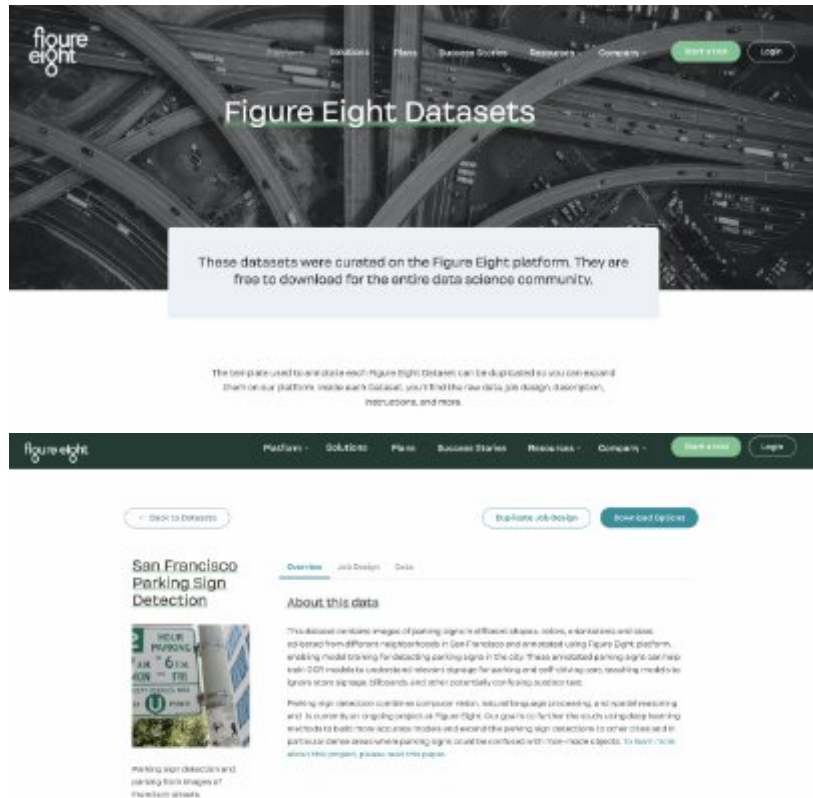
Figure Eight **Human-In-The-Loop** AI platform

Public Dataset

San Francisco street-level imagery

- **Train Images**
 - 1559 images
 - 2257 parking sign annotations
- **Validation Images**
 - 375 images
 - 606 parking sign annotations

www.figure-eight.com/datasets/



Building Deep Models for Parking Sign Recognition

YOLO vs SSD

Active Learning Approach used for Selection of Training Data

You Look Only Once (YOLO)

Used Darknet-19 classification model

- Mostly 3 x 3 filters
- Used batch normalization
- 19 convolutional layers & 5 maxpooling layers
- Initial trained on ImageNet (1000 categories)

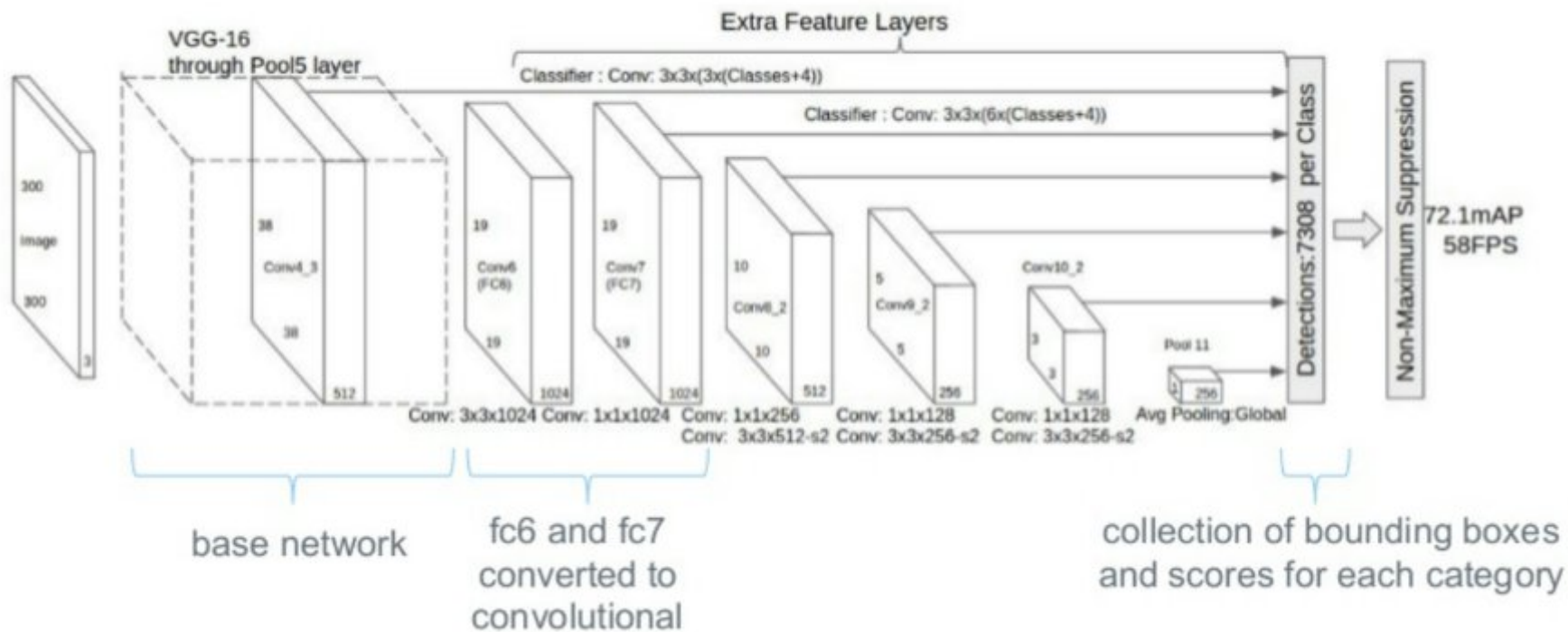
Transfer Learning / Fine Tuning

- Remove last layer and replace with 3 x 3 convolutional layer with 1024 filters followed by 1 x 1 convolutional layer with the number of output
- Epoch is 160

Type	Filters	Size/Stride	Output
Convolutional	32	3 × 3	224 × 224
Maxpool		2 × 2/2	112 × 112
Convolutional	64	3 × 3	112 × 112
Maxpool		2 × 2/2	56 × 56
Convolutional	128	3 × 3	56 × 56
Convolutional	64	1 × 1	56 × 56
Convolutional	128	3 × 3	56 × 56
Maxpool		2 × 2/2	28 × 28
Convolutional	256	3 × 3	28 × 28
Convolutional	128	1 × 1	28 × 28
Convolutional	256	3 × 3	28 × 28
Maxpool		2 × 2/2	14 × 14
Convolutional	512	3 × 3	14 × 14
Convolutional	256	1 × 1	14 × 14
Convolutional	512	3 × 3	14 × 14
Convolutional	256	1 × 1	14 × 14
Convolutional	512	3 × 3	14 × 14
Maxpool		2 × 2/2	7 × 7
Convolutional	1024	3 × 3	7 × 7
Convolutional	512	1 × 1	7 × 7
Convolutional	1024	3 × 3	7 × 7
Convolutional	512	1 × 1	7 × 7
Convolutional	1024	3 × 3	7 × 7
Convolutional	1000	1 × 1	7 × 7
Avgpool		Global	1000
Softmax			

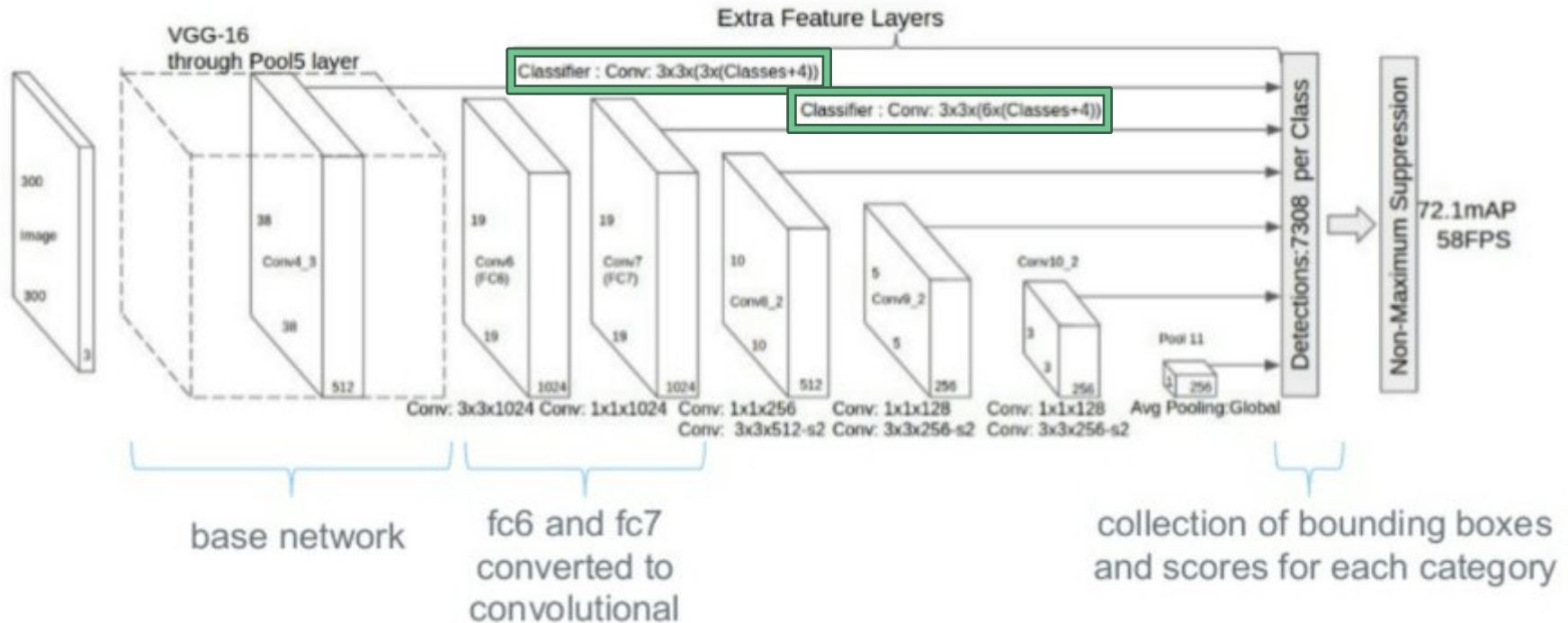
Single Shot Detector (SSD)

Multi-scale feature maps for detection



Single Shot Detector (SSD)

Apply on top of each conv feature map a set of filters that predict object with different aspect ratios and class categories



Active Learning Framework

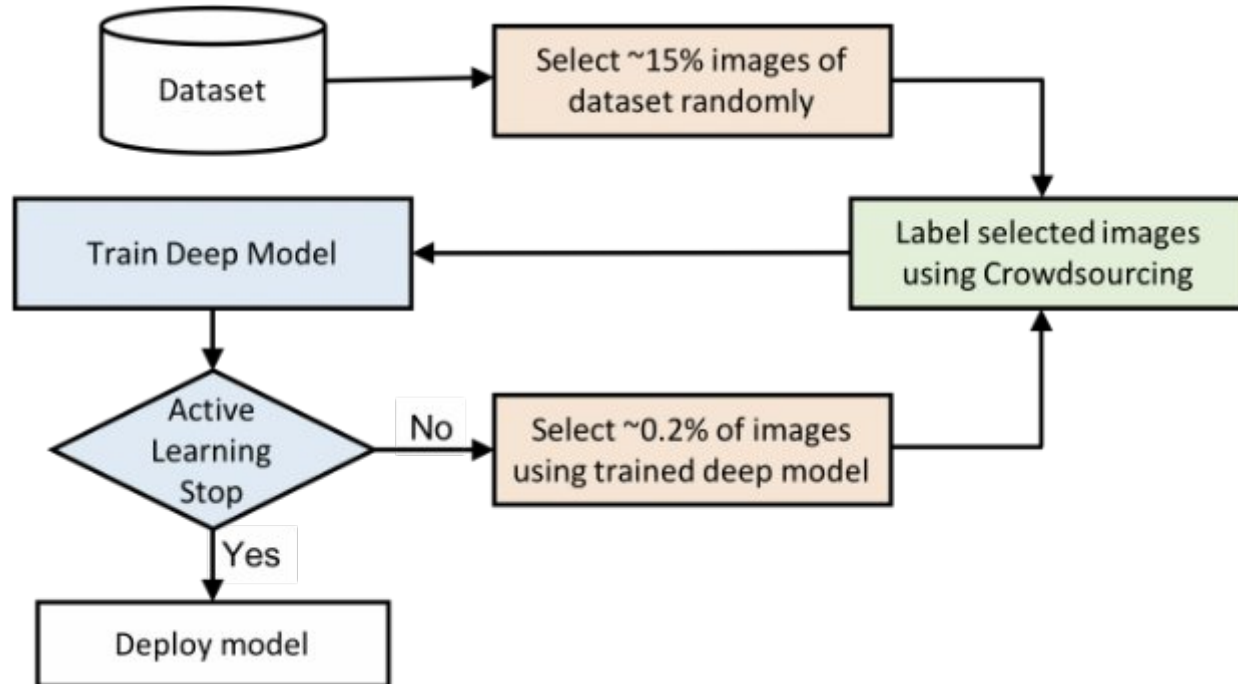
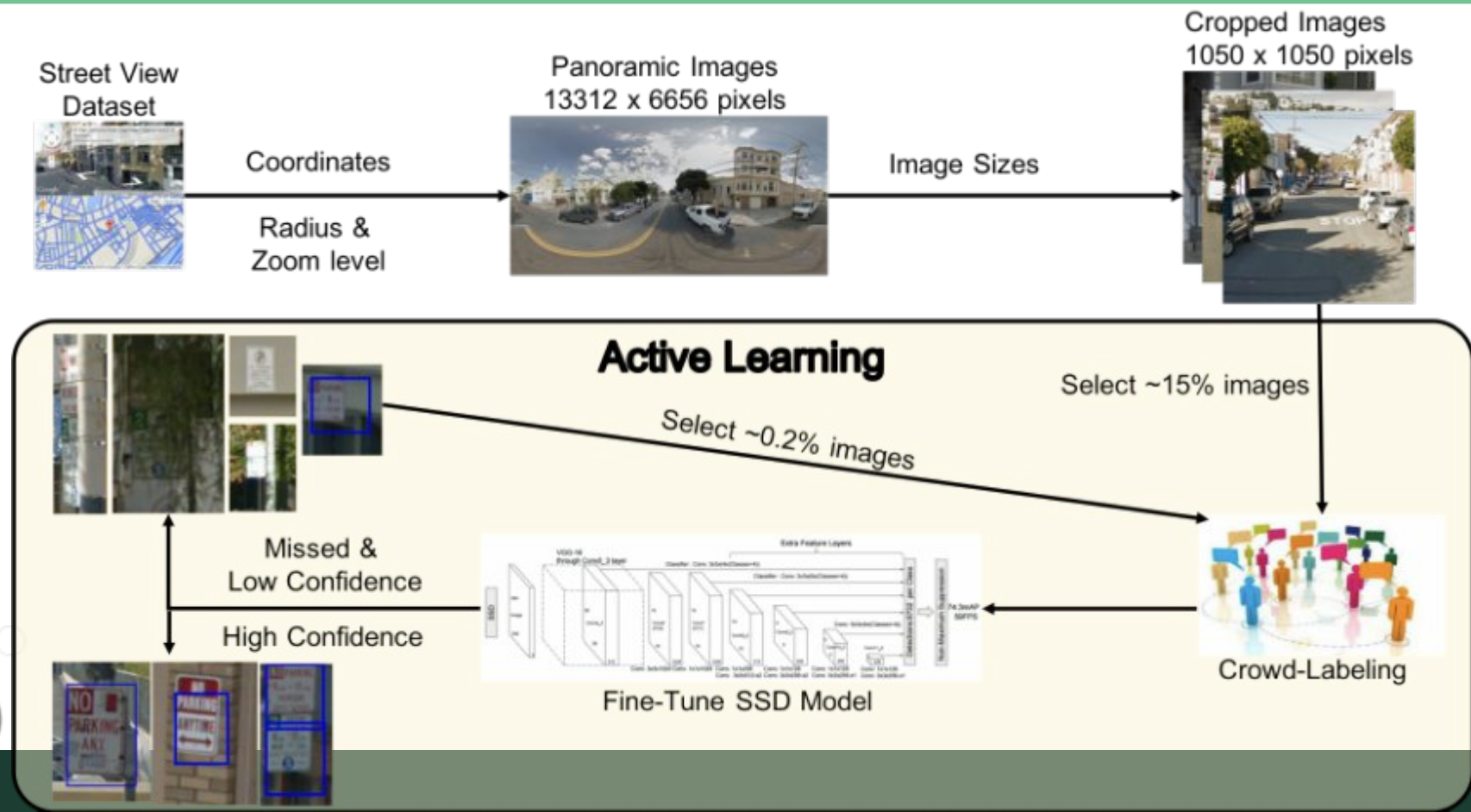


Image Selection and Crowding Labeling

Split Images into three subset and select images for labeling and training the model

- **High Confidence** images which have confidence above 80%
 - Select 20% images from the lowest confidence score
- **Low Confidence** images which have confidence below 80%
 - Select 60% images from highest confidence score
- **No Prediction** images which have no parking sign
 - Select 20% images randomly

Active Learning Framework with Object Detection



Training Sets

Selection of new images in training set using active learning framework

Dataset	No. of Images		No. of Annotations	
	New Addition	Total	New Addition	Total
Test Set	-	375	-	606
Training Set 1	509	509	704	704
Training Set 2	98	607	137	841
Training Set 3	380	987	589	1430
Training Set 4	550	1537	796	2226
Training Set 5	530	2067	893	3119
Training Set 6	400	2467	618	3737
Training Set 7	433	2900	707	4444

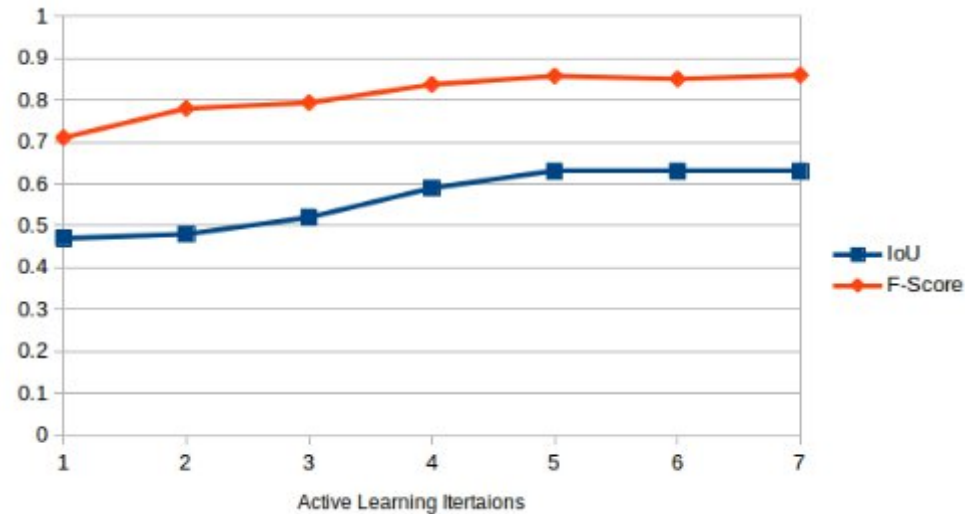
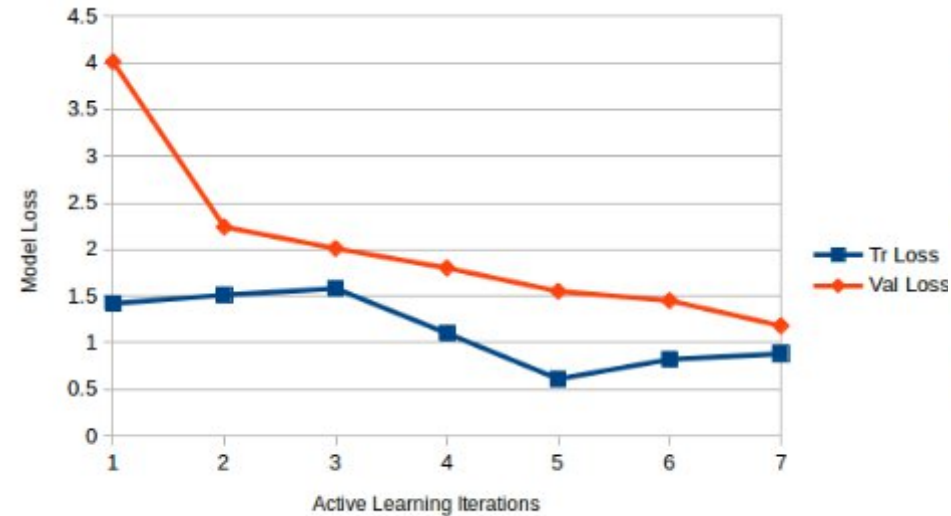
Results

Parking Sign detection results on test set after each iteration of Active Learning Framework

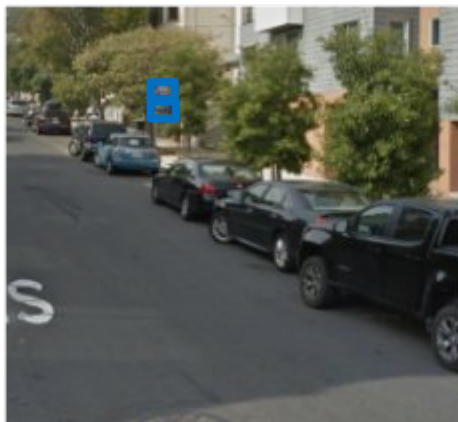
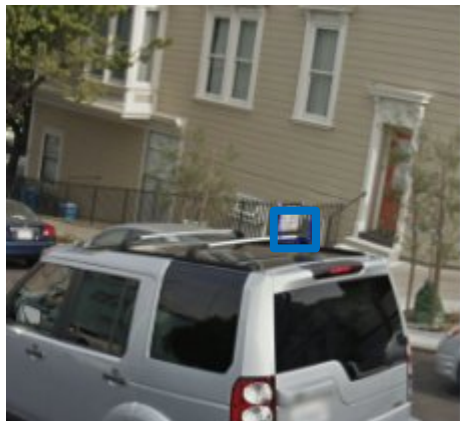
Active Learning Iterations	TP	FN	FP	Recall	Precision	F-Score	IoU
1	397	209	115	0.66	0.78	0.71	0.47
2	413	193	40	0.68	0.91	0.78	0.48
3	417	189	28	0.69	0.94	0.79	0.52
4	452	154	22	0.75	0.95	0.84	0.59
5	493	113	51	0.81	0.91	0.86	0.63
6	477	129	39	0.79	0.92	0.85	0.63
7	476	130	26	0.79	0.95	0.86	0.63

Active Learning Framework Performance

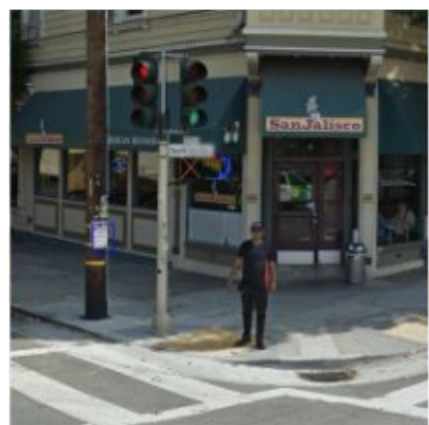
Decrease in model loss and increase in model accuracy



SSD Predictions

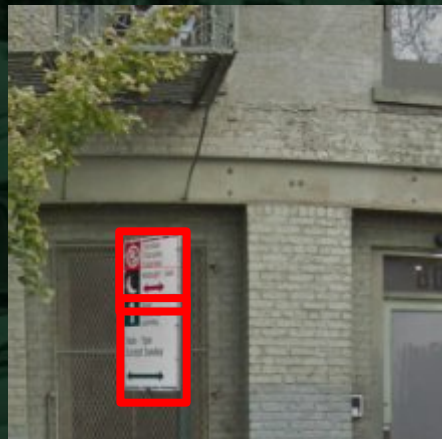


Challenging cases

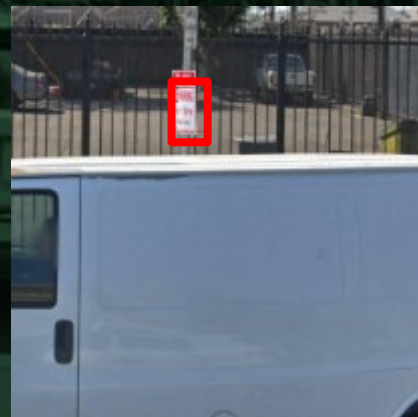


How well does the model work on new data?

New York



Los angeles



Automated Parking Rules Extraction



"NO PARKING AM 012 NOON TUESDAY STREET CLEANING"



"2 HOUR PARKING TO MON THRU SAT EXCEPT VEHICLES WITH PERMITS AREA PARK AT 90 DEGREES"

Improving text analysis results through crowdsourcing



- Detect text bounding boxes
- Extracting text for each box
- Add missing boxes and edit text by crowdsourcing
- Re-train text analysis model using new labeled textboxes

Final Remarks

- Find **challenging cases** where system fails to accurately detect
- Reduce the **redundancy** in training data
- Save **time and cost** for labeling training data
- Improve the model training by better **generalization**

Thank You

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