ASI DATA SCIENCE
STRATA LONDON 2017

Gaining Additional labels

@ASIDataScience

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This presentation reflects my subjective opinions

Supervised learning

- Given
  - Labelled data $\{(features, label)\}$, as $\{(x^l, y^l)\}$
  - Implicitly, a lot of unlabeled data $\{(x, .)\}$
- From the labelled data, inferring a function $f(x)$ for predicting the unknown labels for $\{(x, .)\}$

Semi-supervised learning

- Given
  - Labelled data $\{(features, label)\}$, as $\{(x^l, y^l)\}$
  - Explicitly, a lot of unlabeled data $\{(x, .)\}$
- Inferring a function $y = f(x)$ for predicting the unknown labels for new instances of features, from
  - the labelled data set
  - AND the unlabeled data set

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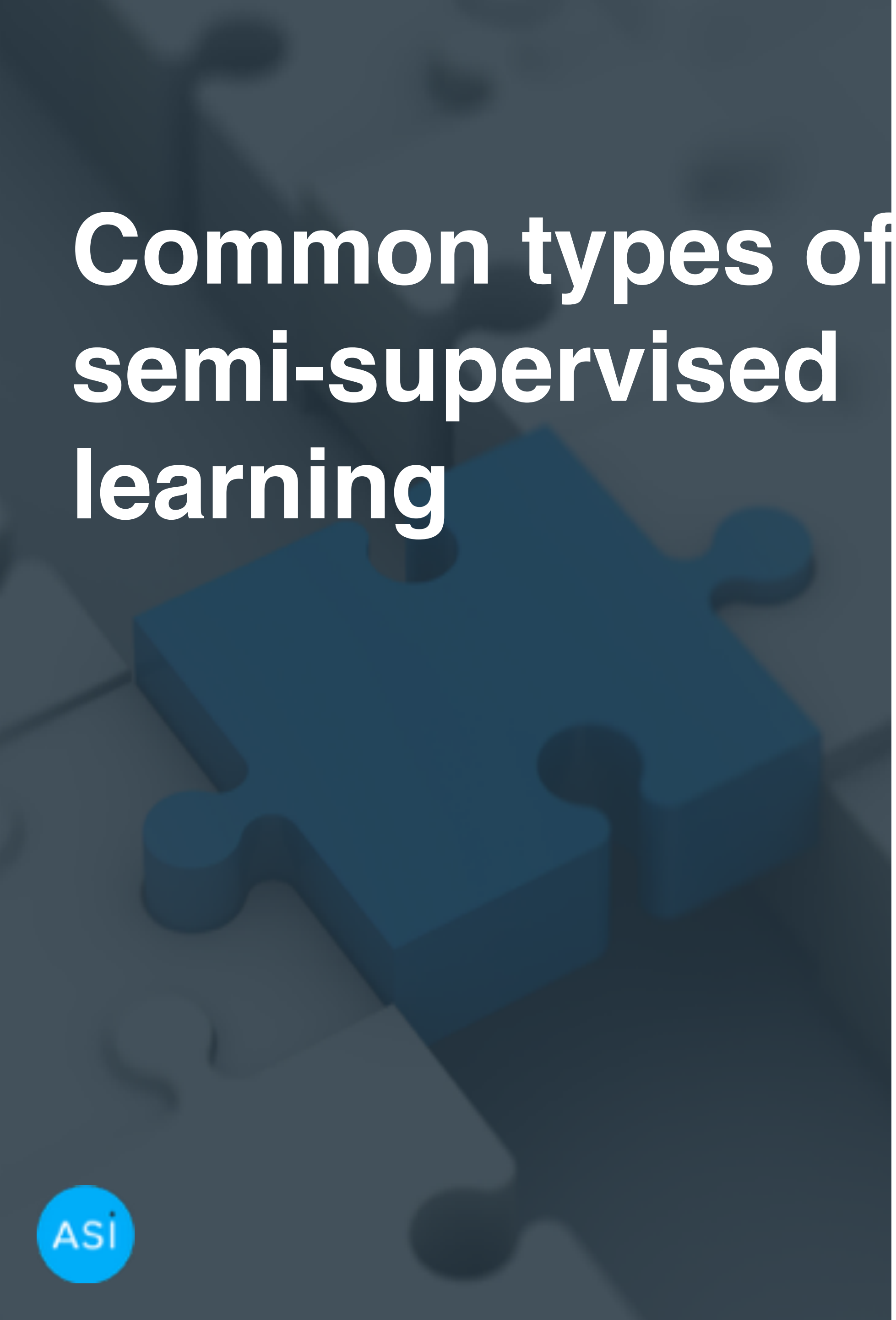
Why bother?

- The performance of your classifier almost always improves with more labelled data.
- labelled data can sometimes expensive, difficult, or time consuming to obtain
- Unlabeled data bear a lot of additional information, for example, the distribution
- Can we improve our performance for free?
- Make use of the unlabeled data – semi-supervised learning

Common types of semi-supervised learning

- Self-training
- Co-training and multi-view learning
- Generative Models

Common types of semi-supervised learning



- Self-training
- Co-training and multi-view learning
- Generative Models
    - strong assumption on the distribution of the data

Self-training

- Wrapper:
  1. Initialize the training set with only the labelled data
  2. Train a classifier $f(x)$ on the training set
  3. Predict on the unlabeled data with $f(x)$
  4. Score $\{(x, f(x))\}$ with the selection metric
  5. Add the m best new instances to the training set
  6. Repeat 2-5 with the enlarged training set

Toy problem demo: Iris data set

- This well-known data set consists of 3 different types of irises of 150 samples
- Each sample has 4 features
- We will only use the first 2 features for 2d visualization purpose

Settings

- Randomly select 15 samples as the labelled data
- The rest, 135 samples, treated as unlabeled data
- Logistic regression
- Code is available at Git Hub
- https://github.com/zysalice/strata_2017_selftraining/blob/master/ToyProblem_iris.ipynb

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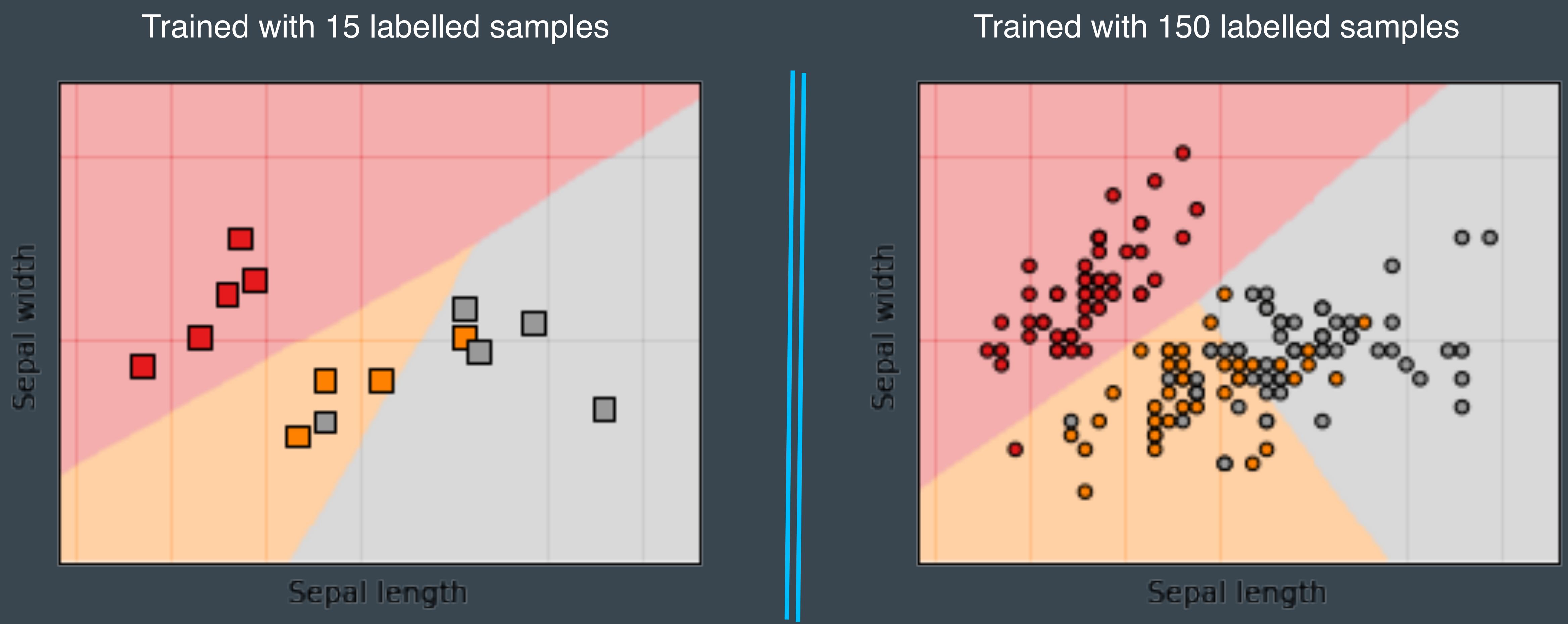
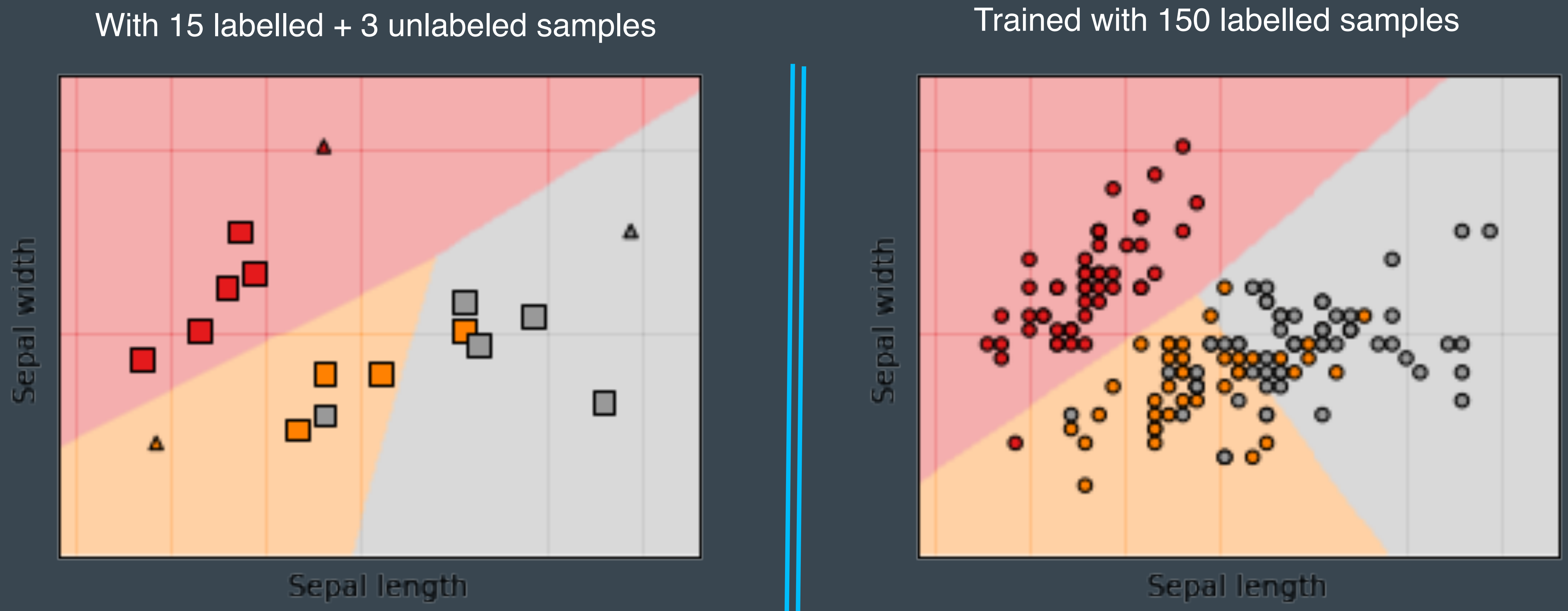
- (x, y)



Comparison of Decision Boundaries

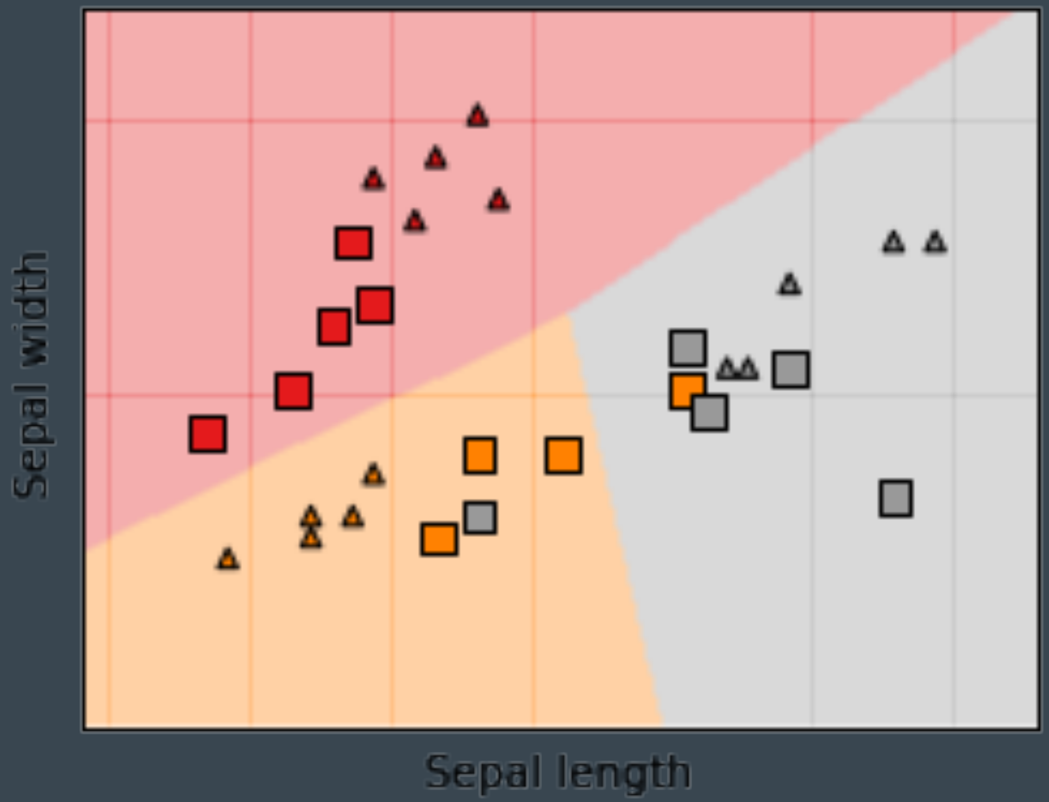
(x, y) $(x, f(x))$



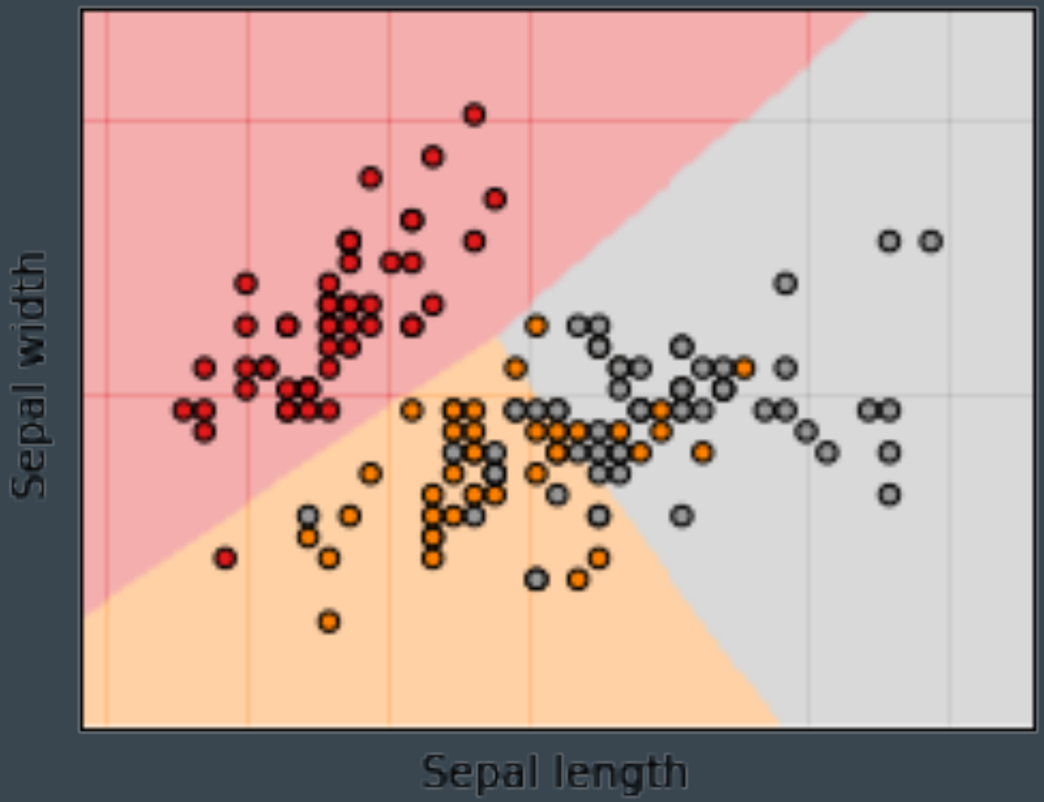
Comparison of Decision Boundaries

(x, y) $(x, f(x))$

With 15 labelled + 15 unlabeled samples



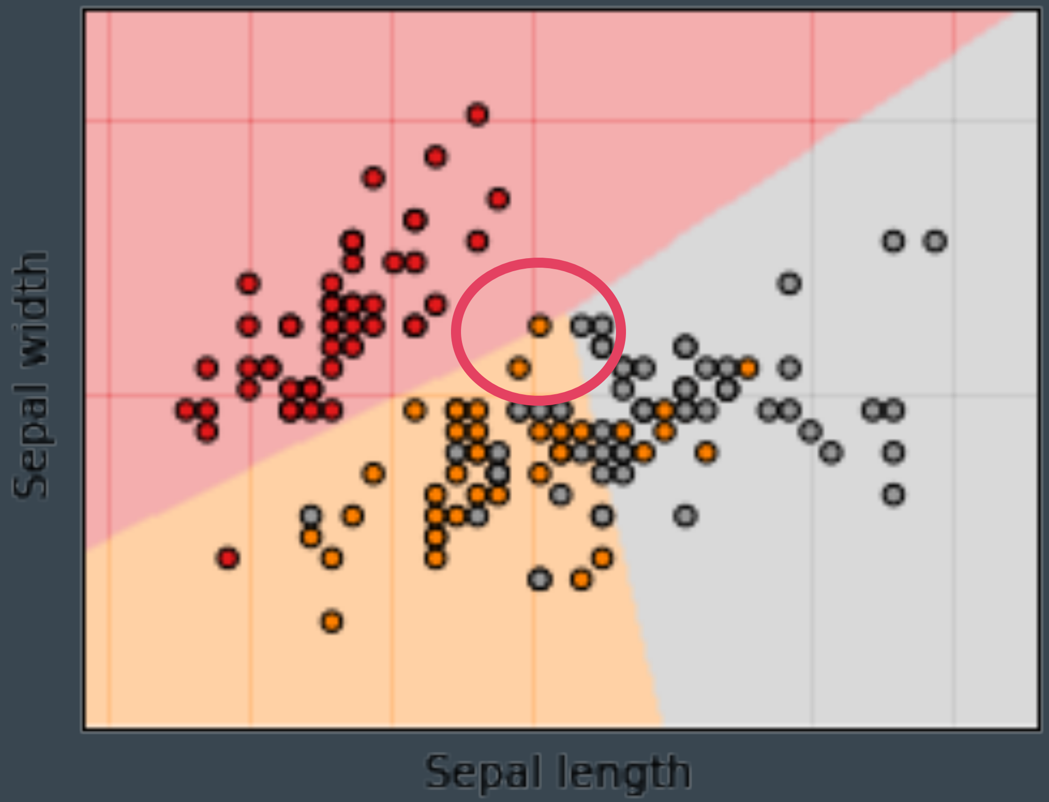
Trained with 150 labelled samples



Comparison of Decision Boundaries

■ (x, y) ▲ $(x, f(x))$

With 15 labelled + 15 unlabeled samples



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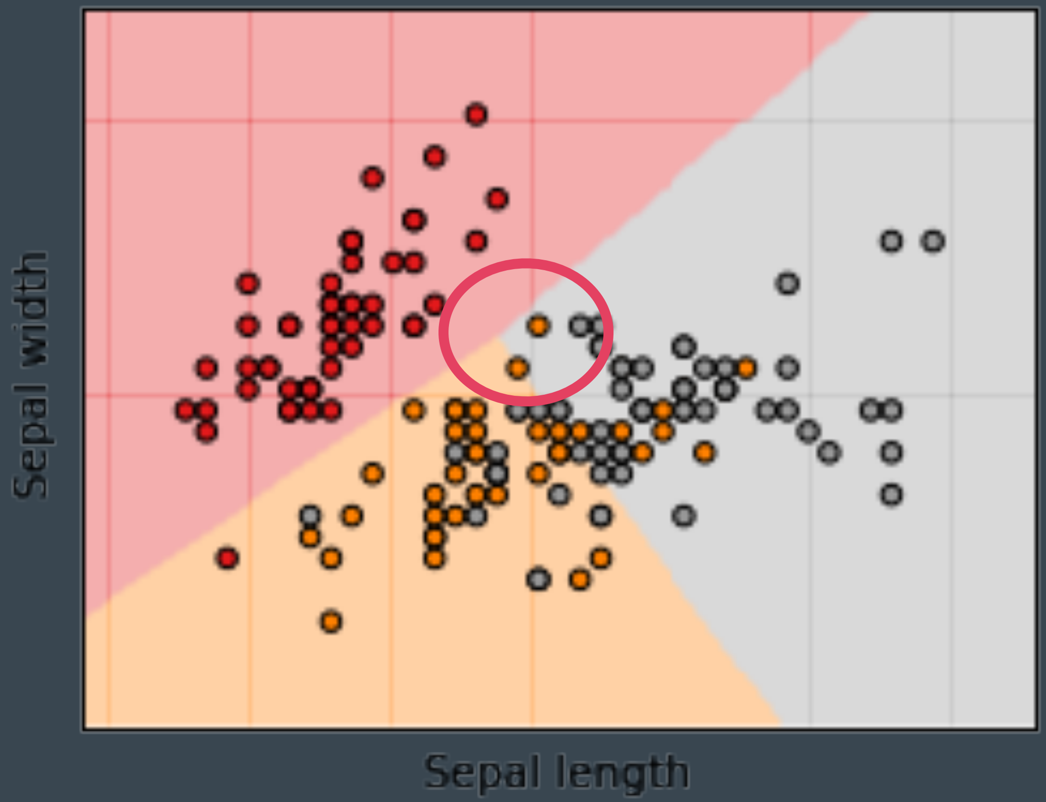


Comparison of Decision Boundaries

Process of unlabeled data selection has a big influence

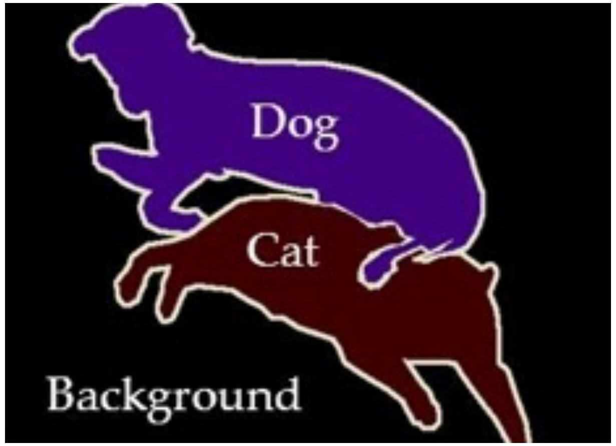
- Only add good instances
  - ➢ include only those points in which the model has high confidence
  - ➢ Use a metric that is independent from the classifier if possible
- Allow bad instances to be deleted
  - ➢ the new classifier doesn’t agree with the old classifier
- Adding and deleting incrementally
  - ➢ the damage of adding/deleting wrong instance is limited

No free lunch

- More effort required to design selection process
- Unlabeled data does not always help
  - ➢ adding incorrect labels can corrupt the model
  - ➢ there are situations that self-training performs badly no matter what
  - ➢ No theoretical guarantee of convergence to better result

Self-training in CNN semantic image segmentation

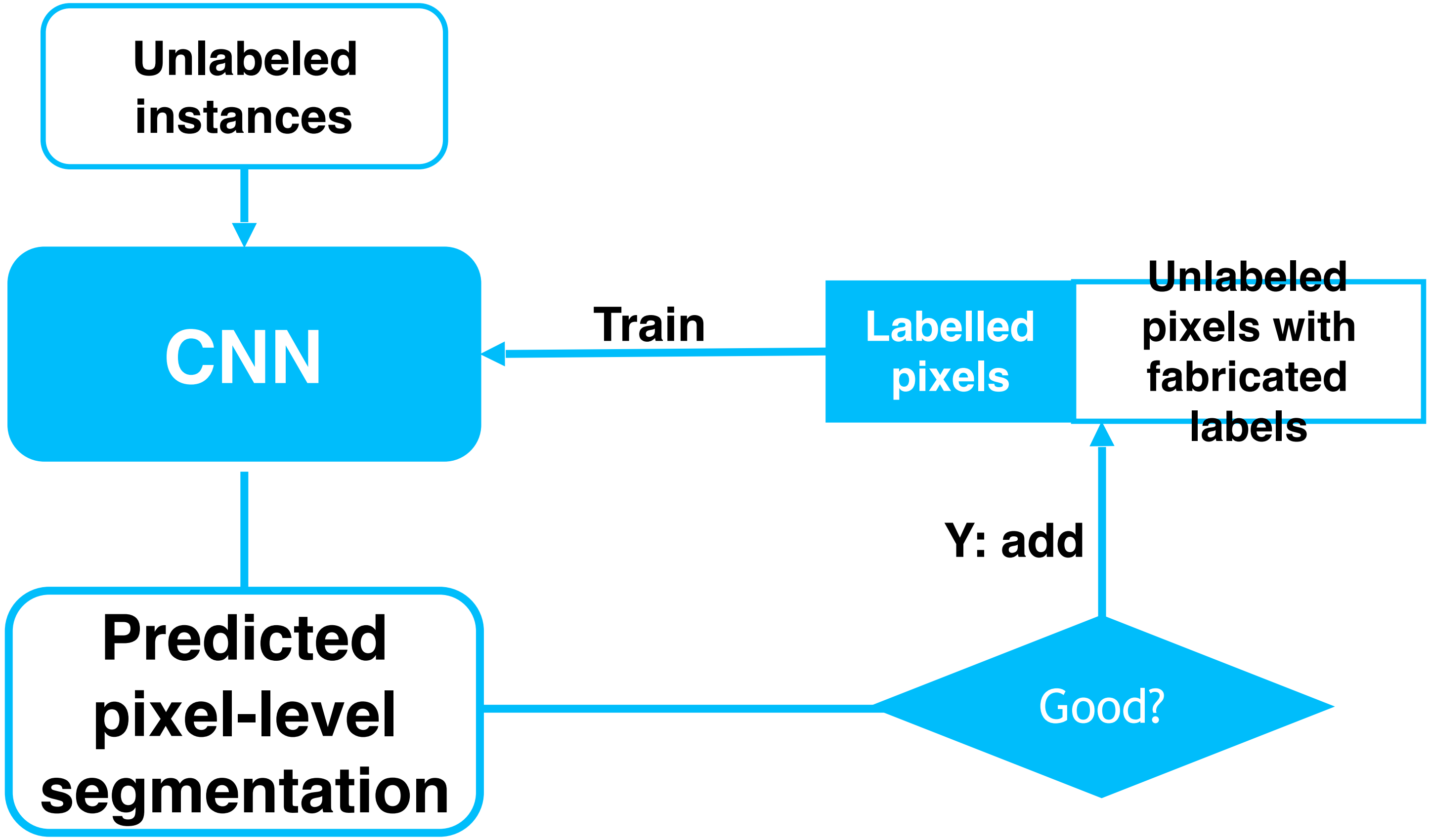
“Fully convolutional networks for semantic segmentation” Long et al, CVPR2015



- Image goes in
- Labels **for each pixel** come out
- Training set: images with pixel-level annotation - expensive

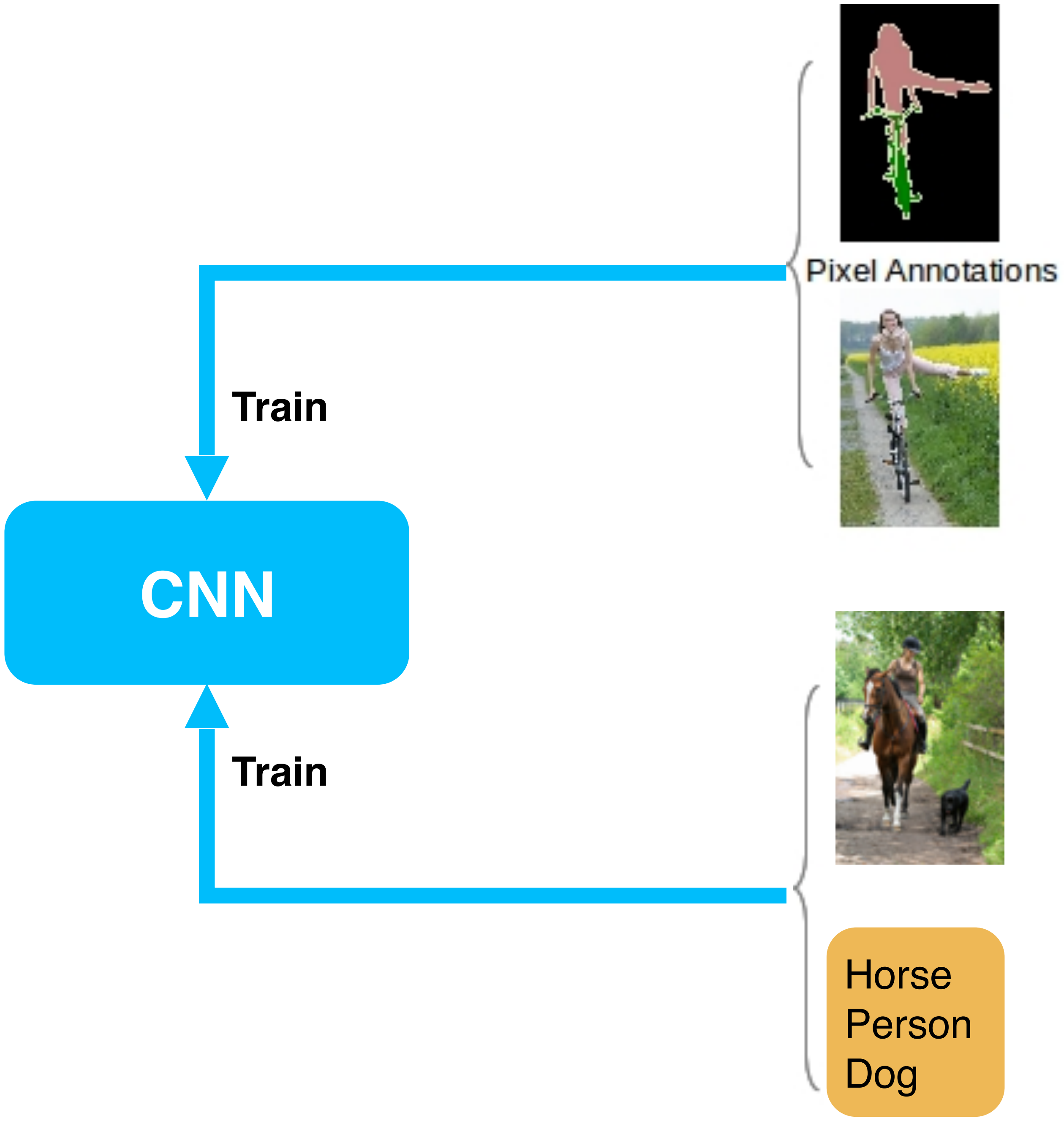
Self-training with CNN

- Start from a basic CNN for semantic segmentation



Semantic Image segmentation (common scene)

- Papandreou, George, et al. "Weakly-and semi-supervised learning of a DCNN for semantic image segmentation." arXiv preprint arXiv: 1502.02734 (2015).



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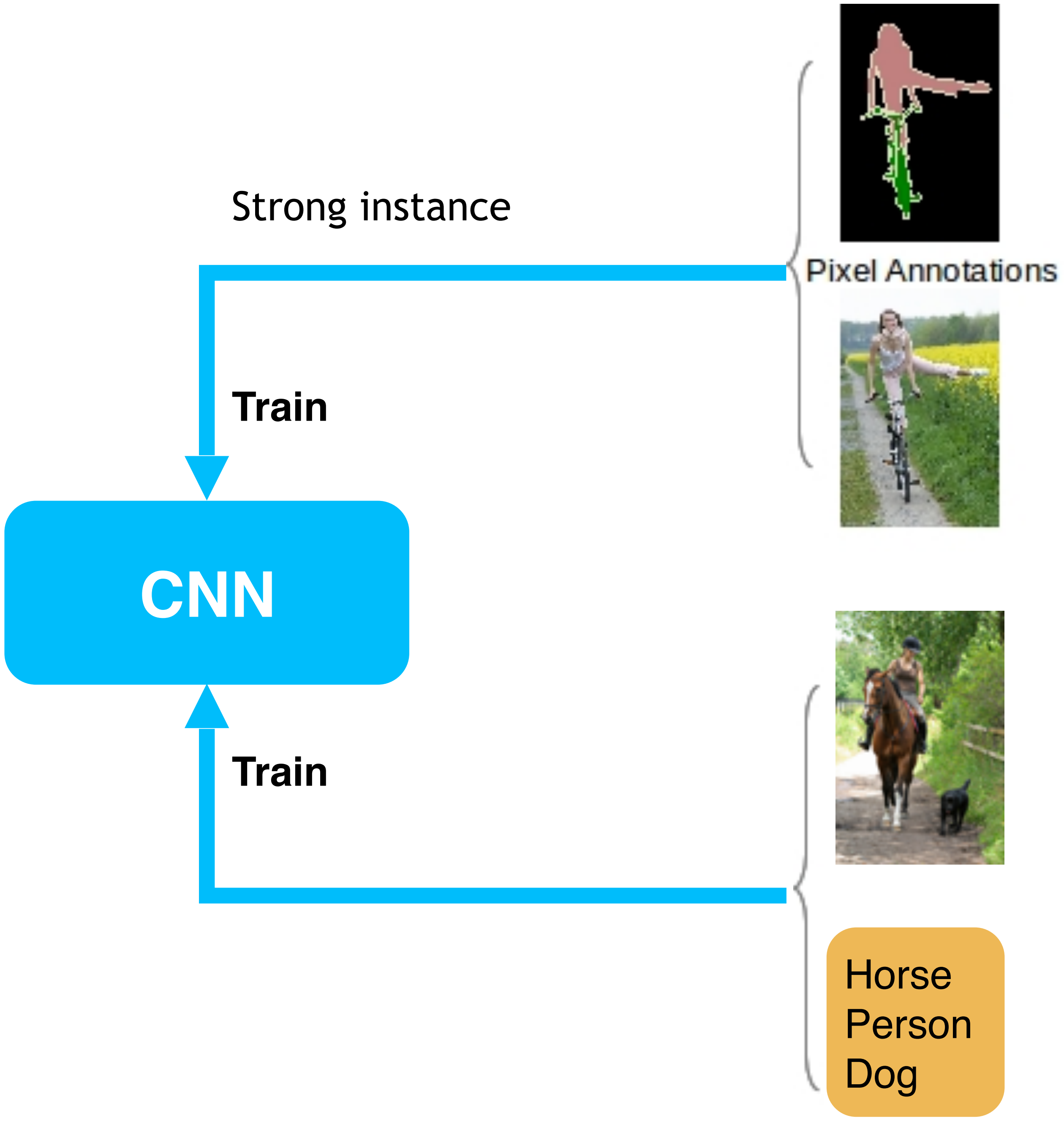

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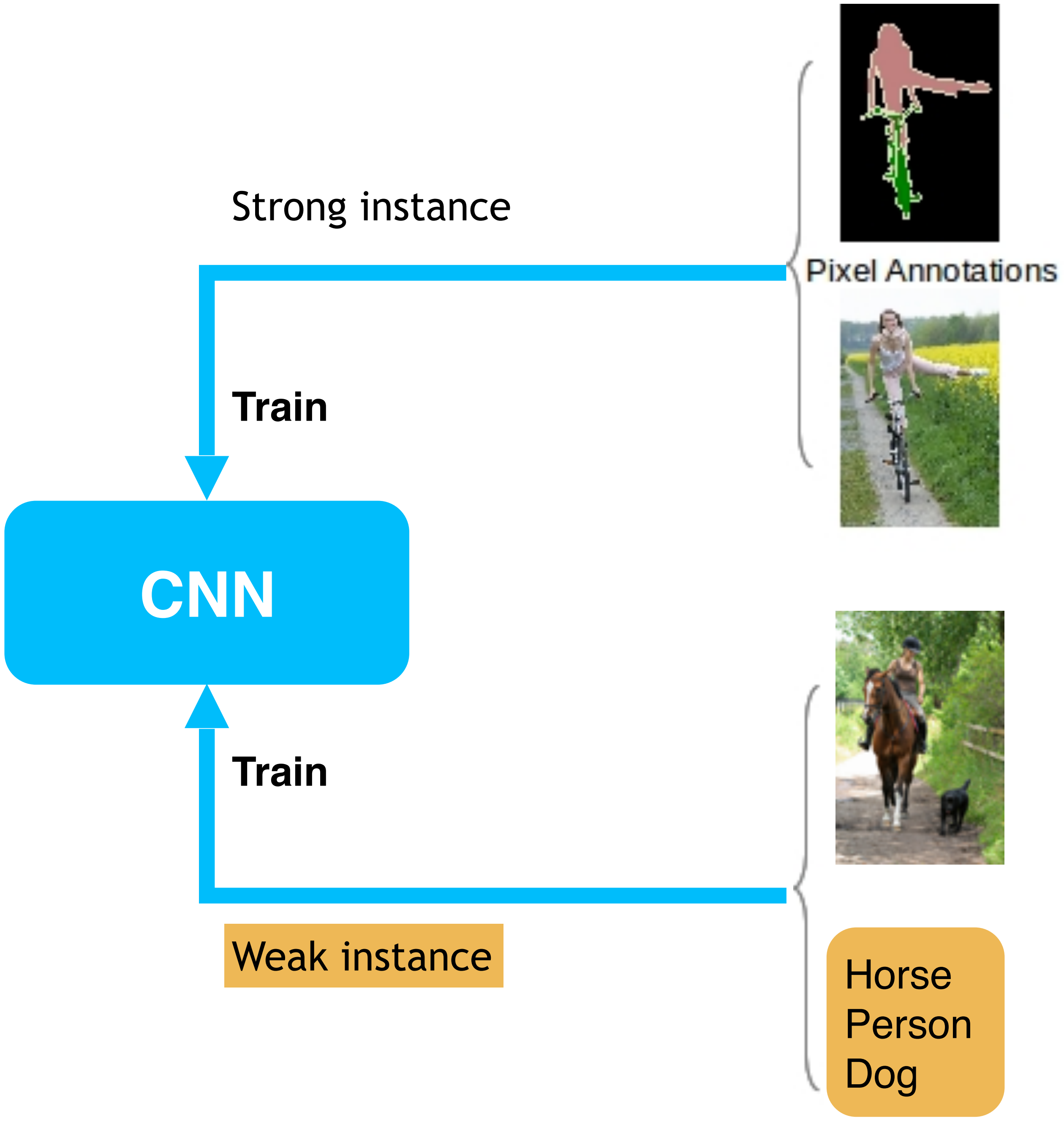

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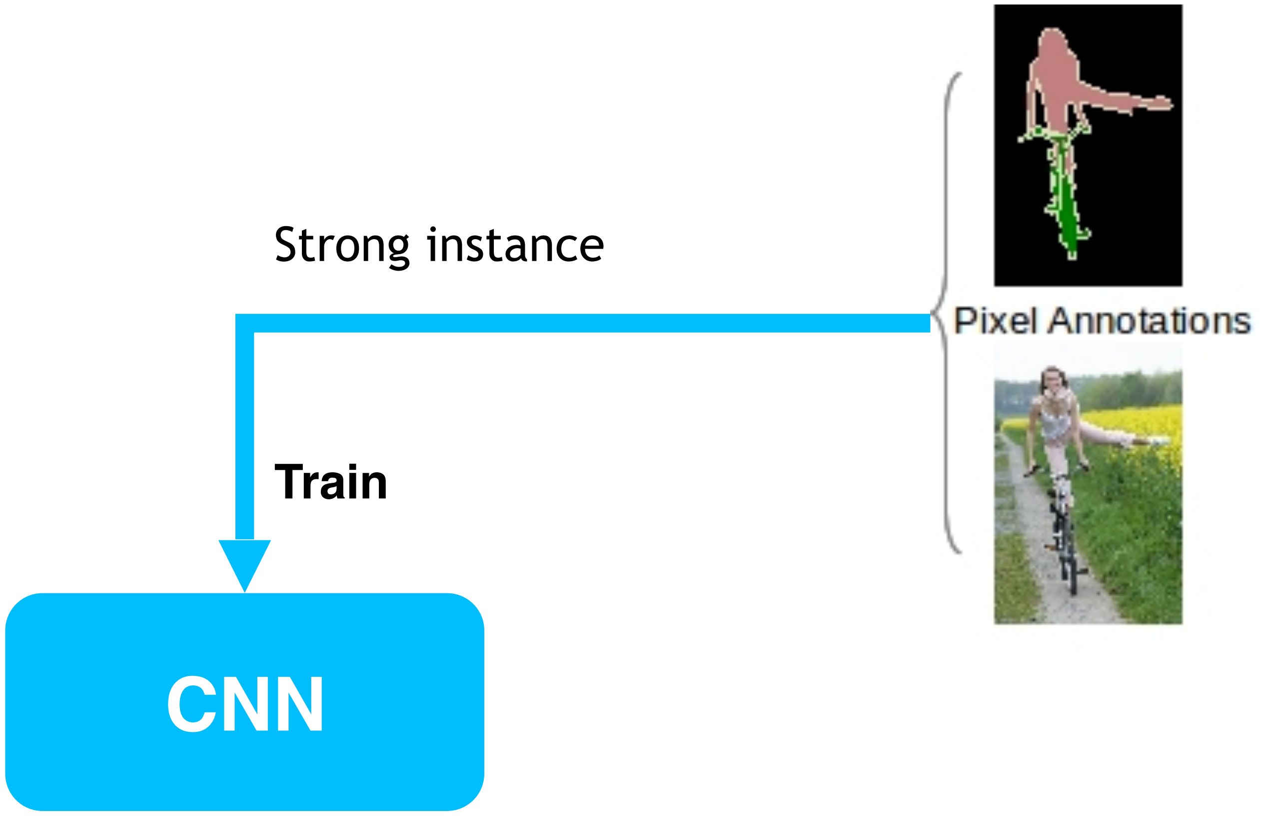

- Train an CNN with the strong instance
- The cost function is the cross-entropy function

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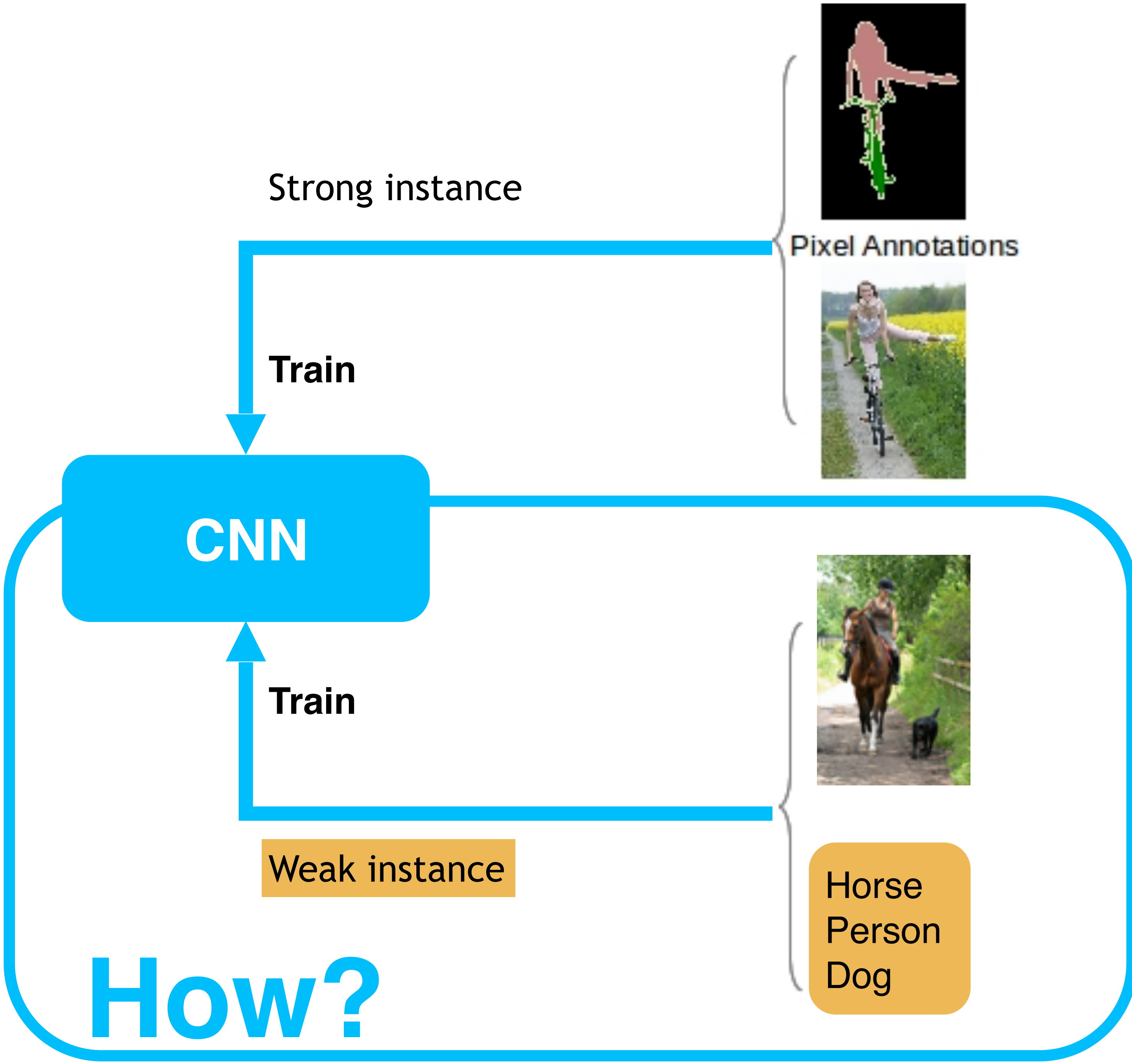

Semantic Image segmentation (common scene)

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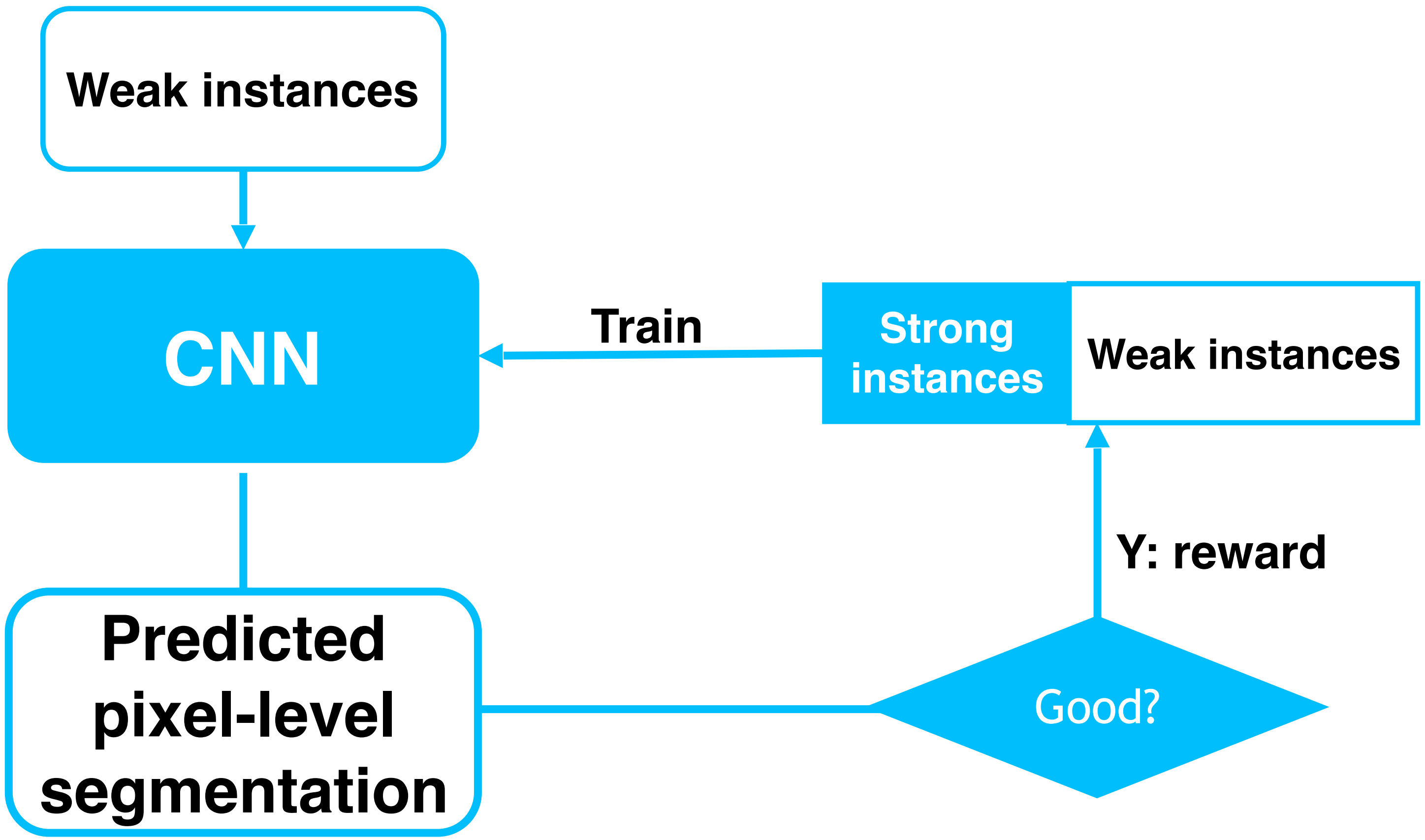
- Use the self-training wrapper



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Semantic Image segmentation (common scene)

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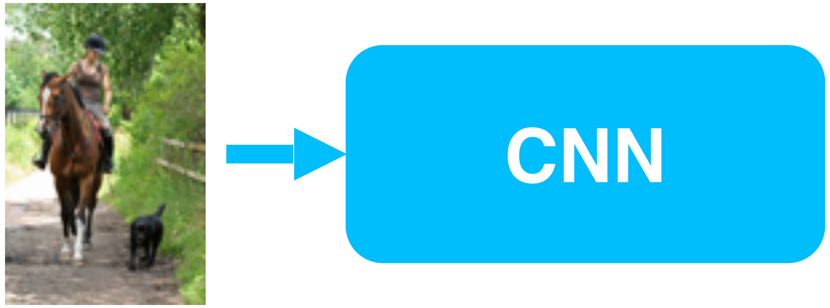
- Put the unlabeled image into the CNN



Log of per-pixel label distribution at location m

$$f_m(y_{m,l}|x;\theta)$$

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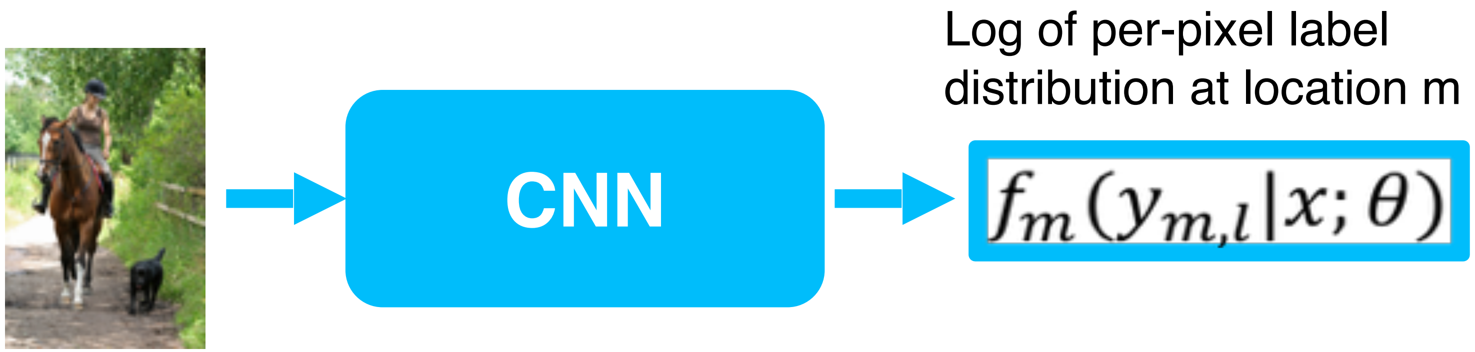

- For every pixel m, do the following to $f_m(y_{m,l}|x;\theta)$:

$$\begin{cases} f_m(y_{m,l}|x;\theta)+c, & if\ y_{m,l}\in\{person, horse, dog\} \\ f_m(y_{m,l}|x;\theta), & otherwise \end{cases}$$

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Semantic Image segmentation (common scene)

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- Put the unlabeled image into the CNN

→ **CNN** → $\boxed{f_m(y_{m,l}|x;\theta)}$

Log of per-pixel label distribution at location m

- For every pixel m, do the following to $f_m(y_{m,l}|x;\theta)$:

Reward

Weak labels for this image

$$\begin{cases} f_m(y_{m,l}|x;\theta) + c, & if\ y_{m,l} \in \{person, horse, dog\} \\ f_m(y_{m,l}|x;\theta), & otherwise \end{cases}$$

Semantic Image segmentation (common scene)

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CNN

Log of per-pixel label distribution at location m

$\boxed{f_m(y_{m,l}|x;\theta)}$

- For every pixel m, do the following to $f_m(y_{m,l}|x;\theta)$:

$$\begin{cases} f_m(y_{m,l}|x;\theta) + c, & \text{if } y_{m,l} \in \{person, horse, dog\} \\ f_m(y_{m,l}|x;\theta), & otherwise \end{cases}$$

- The loss function becomes

$$\mathrm{L}(\theta) = -\sum_m \max_l f_m(y_{m,l}|x;\theta)$$

-- cross-entropy

Improved performance by semi-supervised learning

	# Strong	#weak	Dice measure
supervised	15582	-	0.687
	10582	-	0.676
	1464	-	0.625
semi-super	1464	9118	0.646
	10582	123287	0.677
	15582	118287	0.700

- Papandreou, George, et al. "Weakly-and semi-supervised learning of a DCNN for semantic image segmentation." arXiv preprint arXiv:1502.02734 (2015).

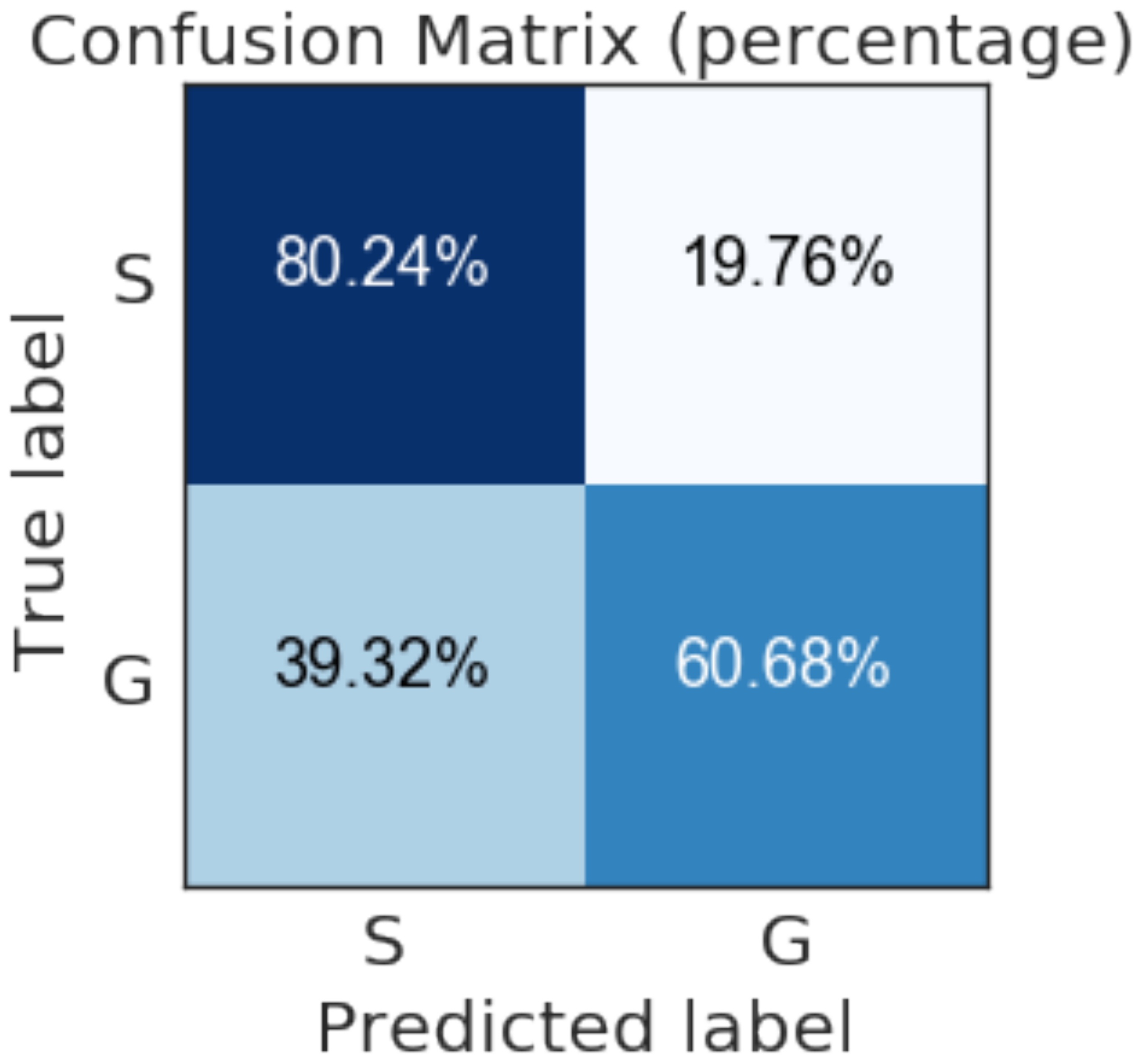
Self-training in feature engineering

Filtering twitter message

- Twitter is a great source for information
- After scraping, we filtered twitter message using keywords
- Human experts labelled a small portion of the data with ’Spam’ (68%) and ‘Good’ (32%)
- Purpose:
    - develop an algorithm for filtering out the spams.

Naïve Bayesian spam filter

- A simple Naïve Bayesian spam filter seems to perform reasonably well



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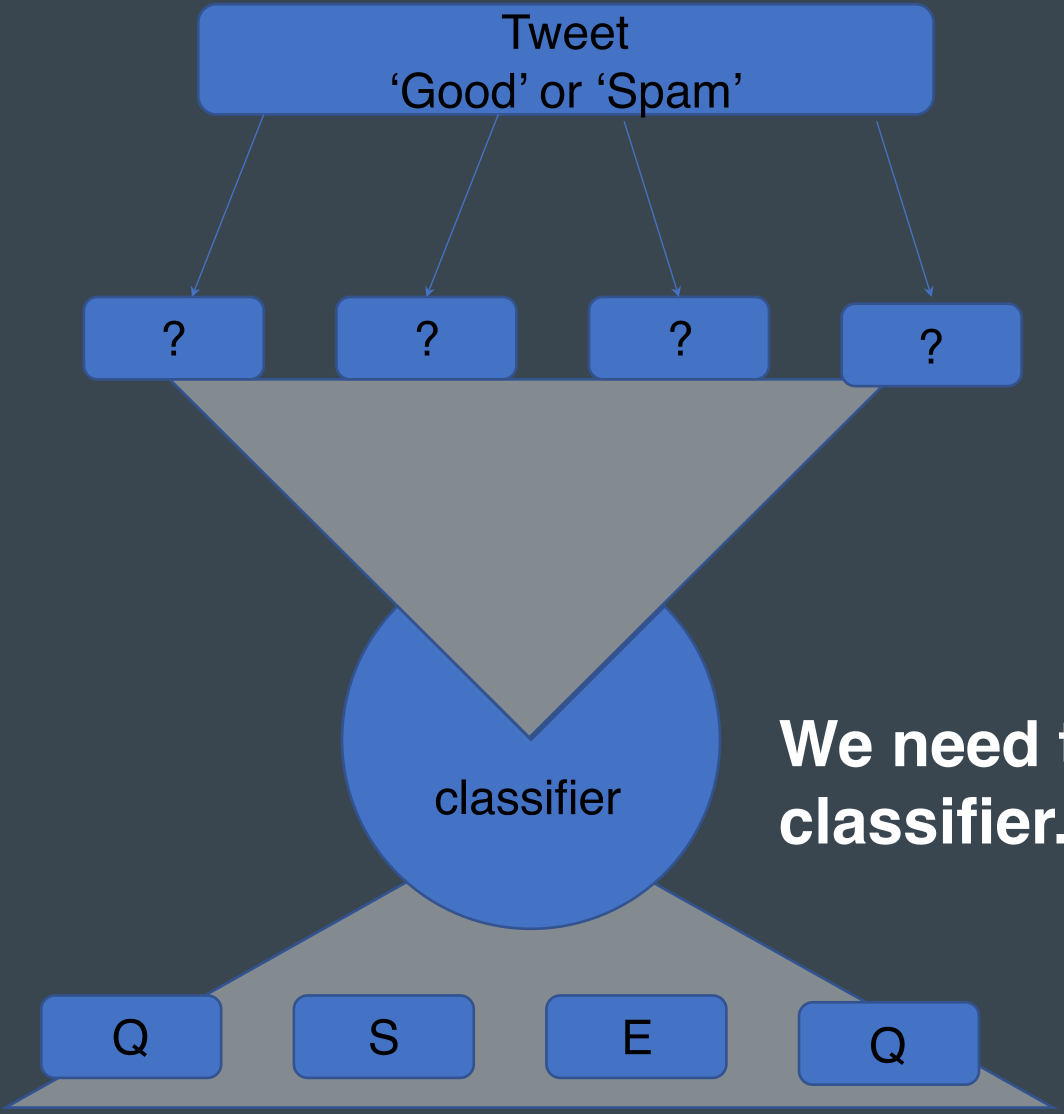
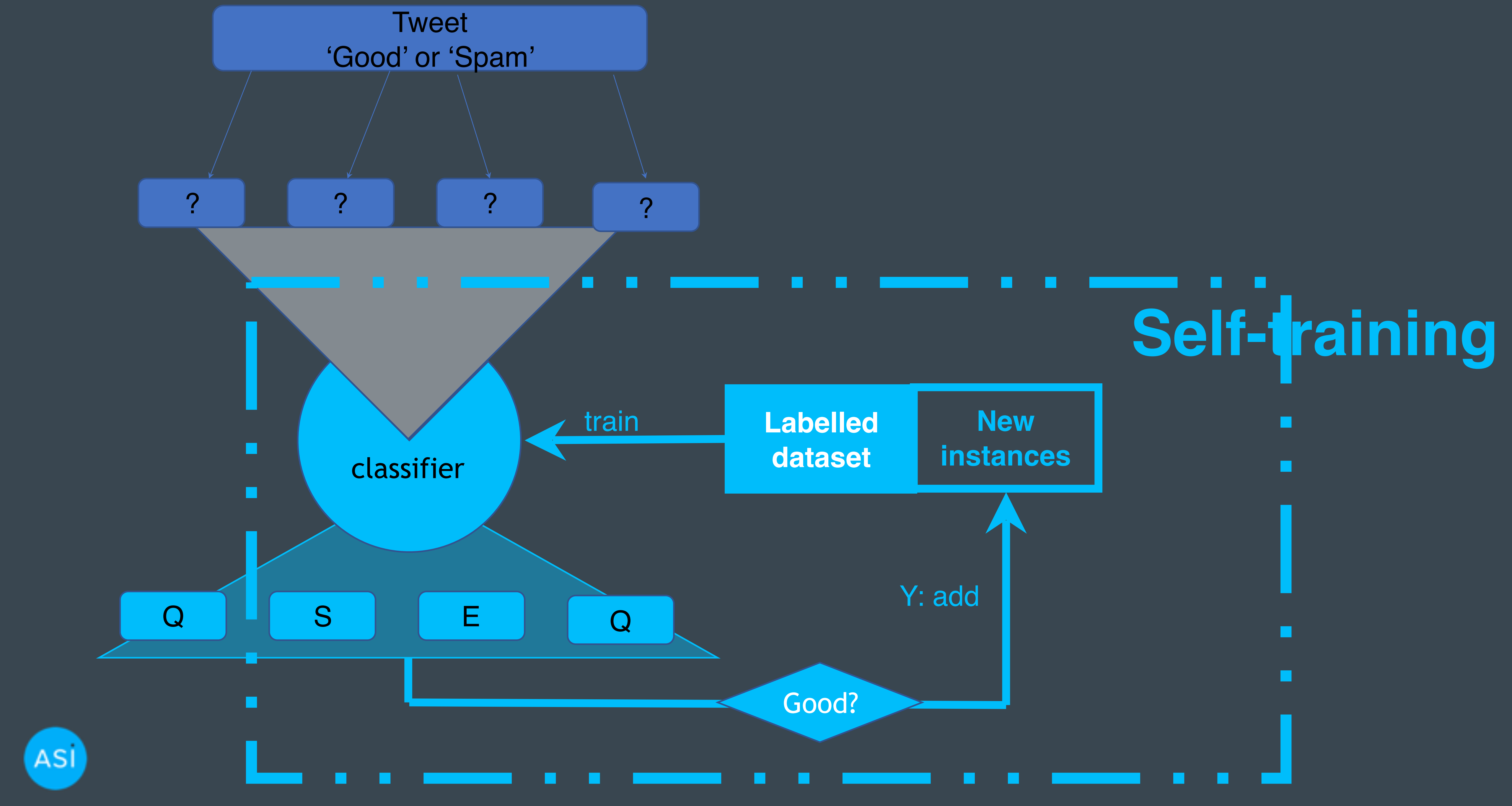
How can we improve

- More features than just ‘words’
  - A lot of ’Good’ tweets contain questions and statements
  - The new features:
    - the proportion of question, statement, emotion or others
    - Semantic level features – we don’t have labels



question, statement, emotion or other?

We need to train this classifier.


Tweet
'Good' or 'Spam'
?
?
?
?
Self-training
train
Labelled dataset
New instances
classifier
Y: add
Q
S
E
Q
Good?
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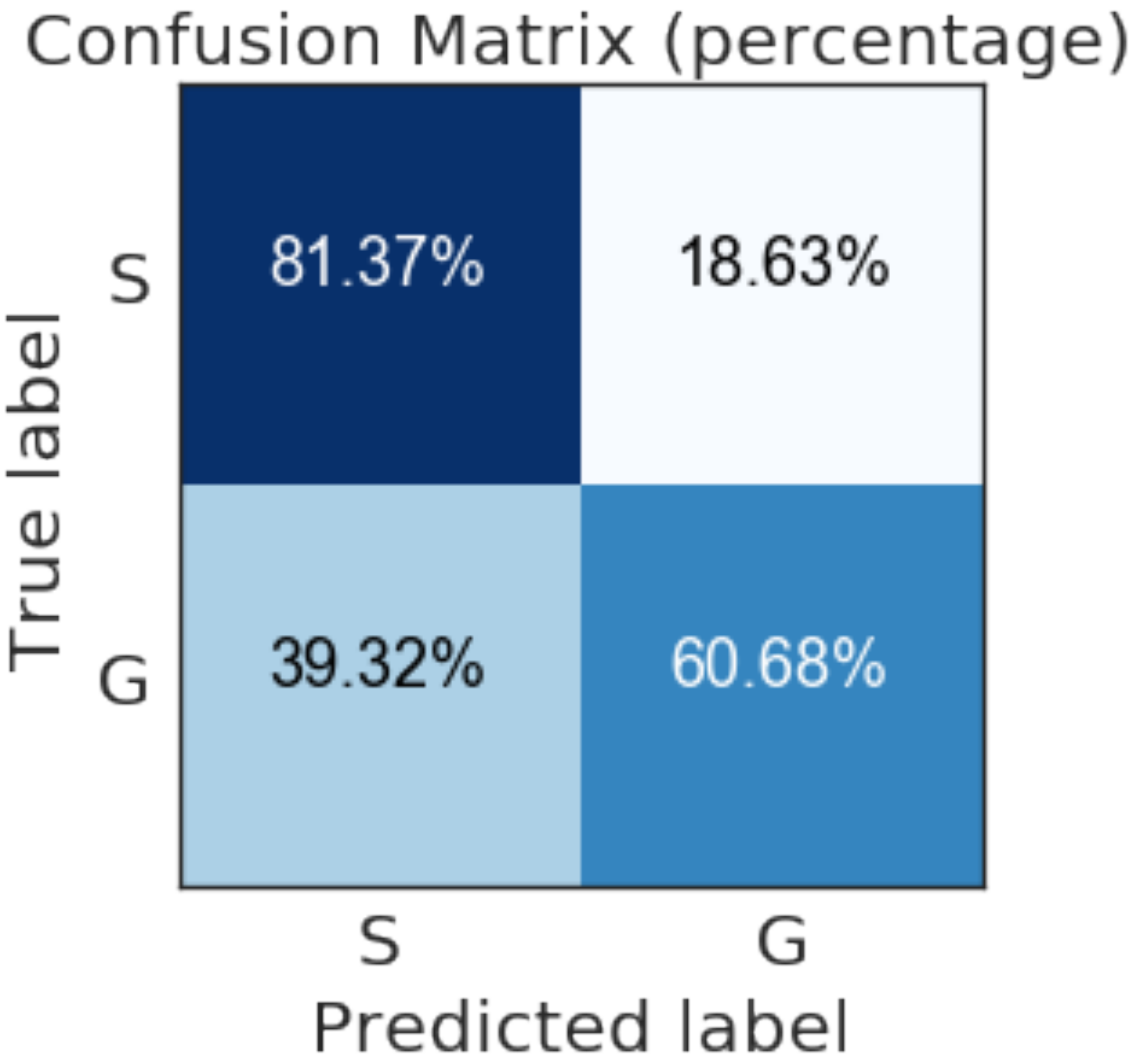
Prediction with augmented features from semi-supervise learning

- Reduced False positive rate from 19.76% → 18.63%



A few more words…

- If possible, get more labelled data
- **Beware of overfitting when using complicated models**
- A lot of effort required
- It won’t always help

SHERLOCKML

https://sherlockml.com

Invite code: *Strata2017*

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