

# Uncertainty in Semi-Supervised Learning

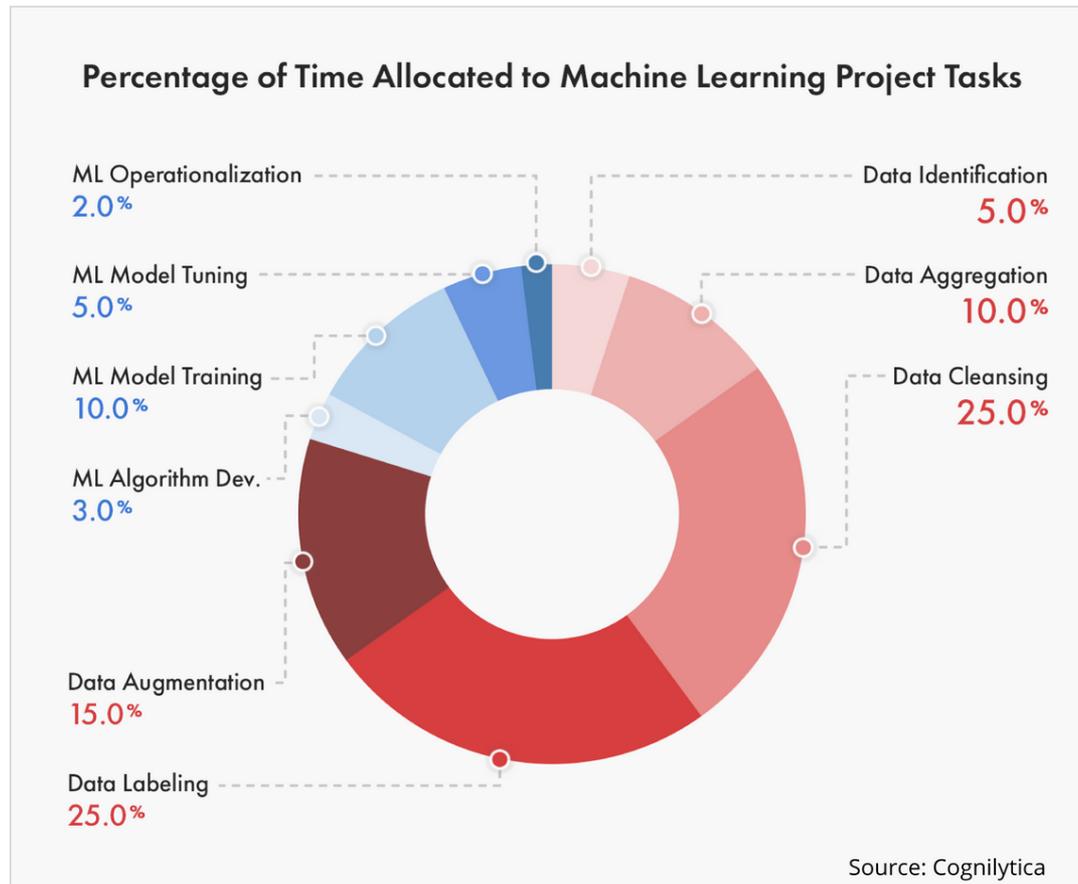
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2. Basics
3. Certainty-Driven Consistency Loss for Semi-supervised Learning
  1. Architecture
  2. Uncertainty in neural networks
  3. Integration of Uncertainty
  4. Experiments
4. Conclusion

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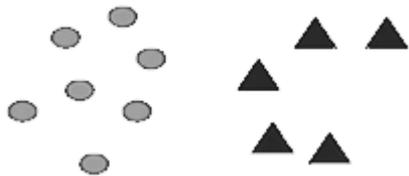
# Labeling Data



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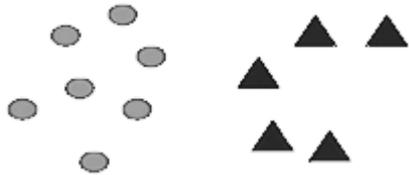
# Semi-supervised Learning



Labeled Data

Source: <https://medium.com/dataseries/two-minutes-of-semi-supervised-learning-f0eb62729530>

# Semi-supervised Learning



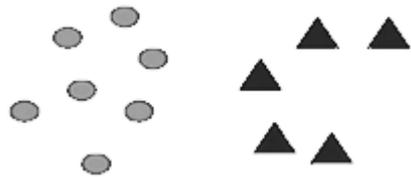
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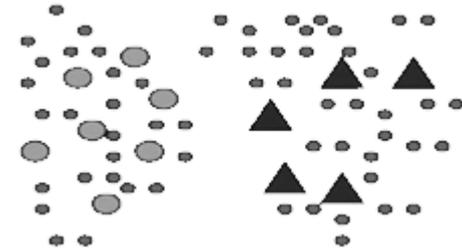
Supervised Learning

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# Semi-supervised Learning



Labeled Data

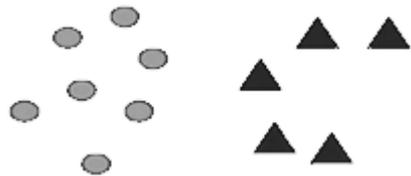


Labeled and  
Unlabeled Data

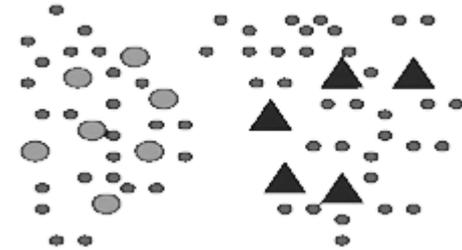


Supervised Learning

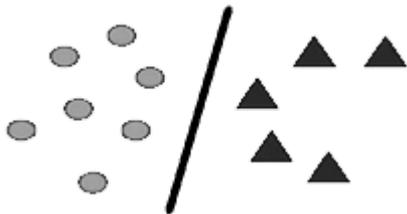
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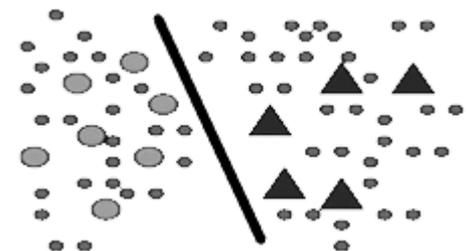
Labeled Data



Labeled and Unlabeled Data



Supervised Learning

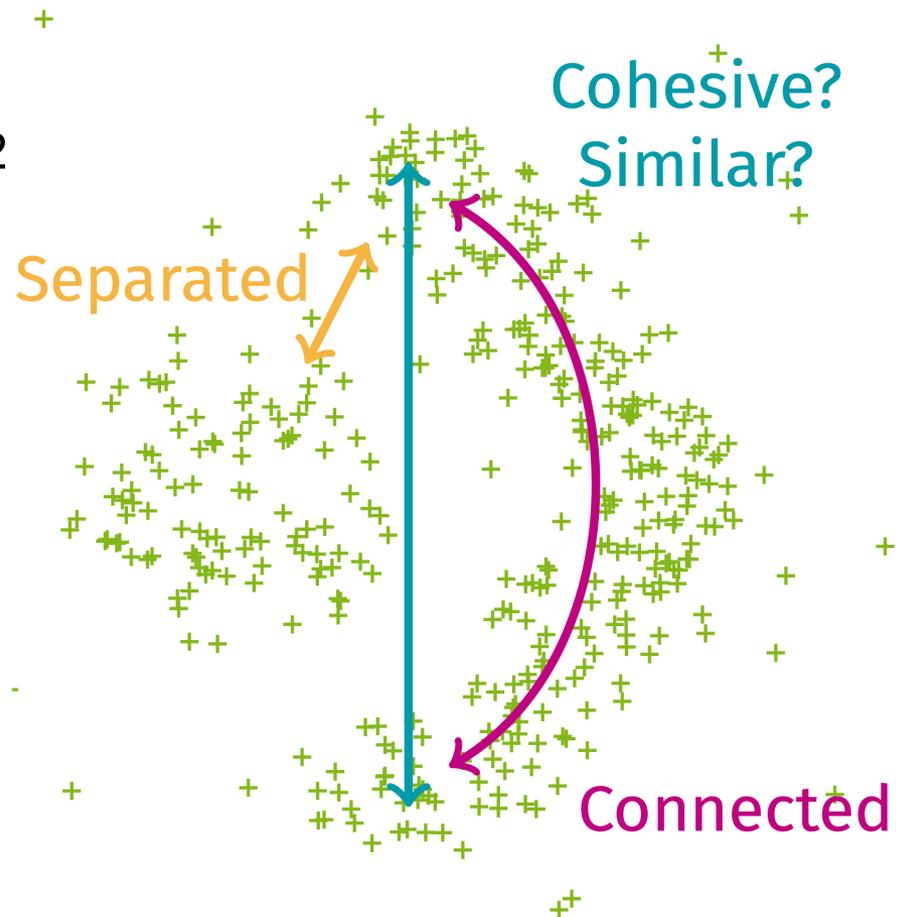


Semi-Supervised Learning

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# Smoothness Assumption

If two points  $x_1$  and  $x_2$  are close, then so should be the corresponding outputs  $y_1$  and  $y_2$ .

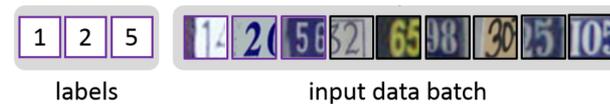


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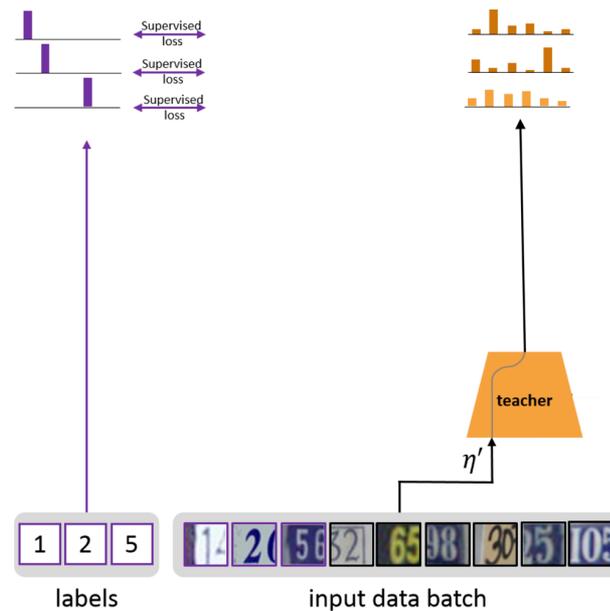
# Architecture

- Partly labeled Dataset



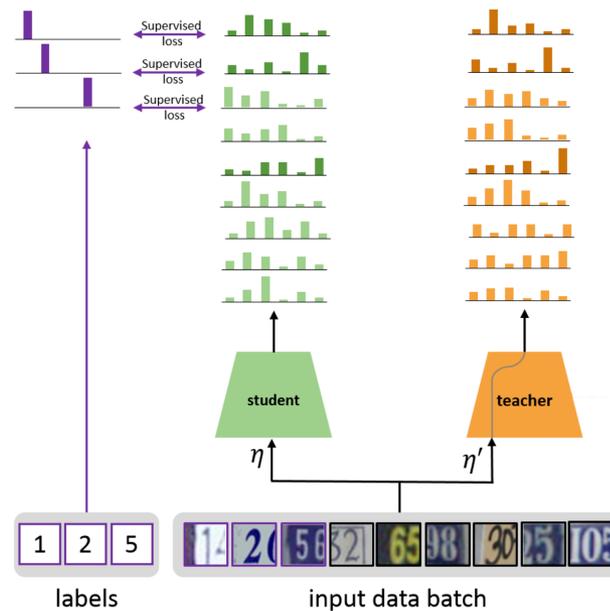
# Architecture

- Partly labeled Dataset
- Supervised teacher network



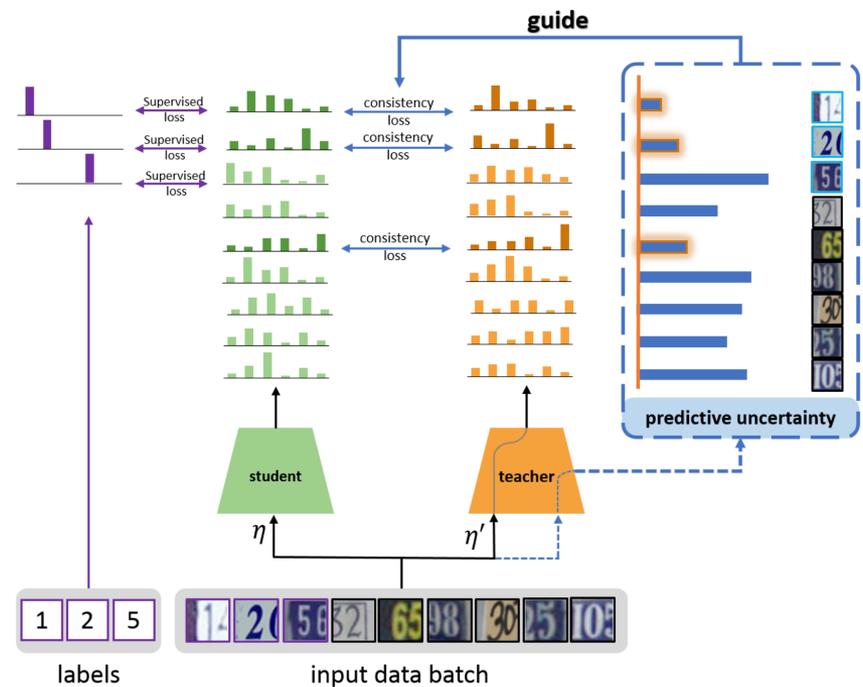
# Architecture

- Partly labeled Dataset
- Supervised teacher network
- „Trained“ student network



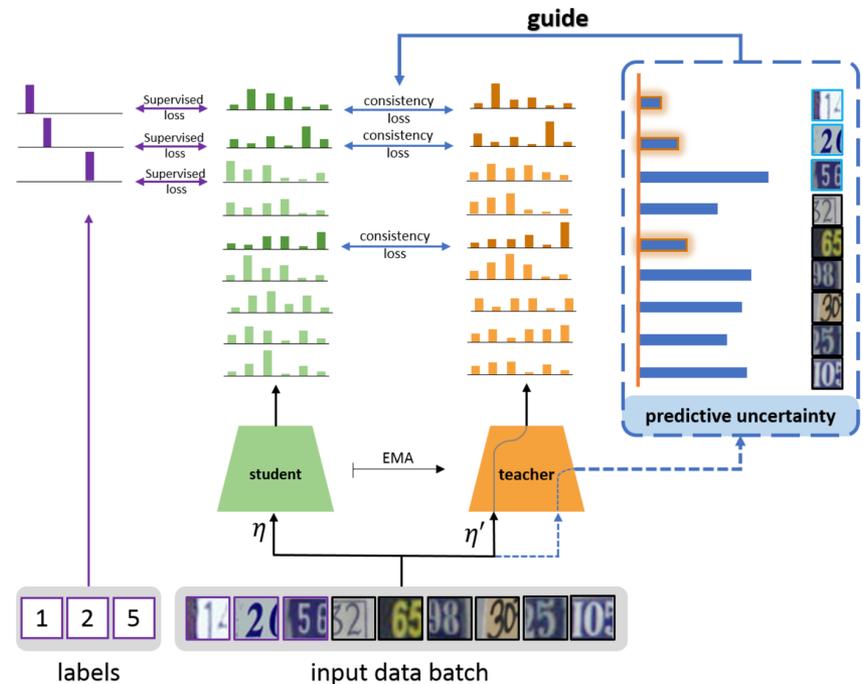
# Architecture

- Partly labeled Dataset
- Supervised teacher network
- „Trained“ student network
- Uncertainty measurement



# Architecture

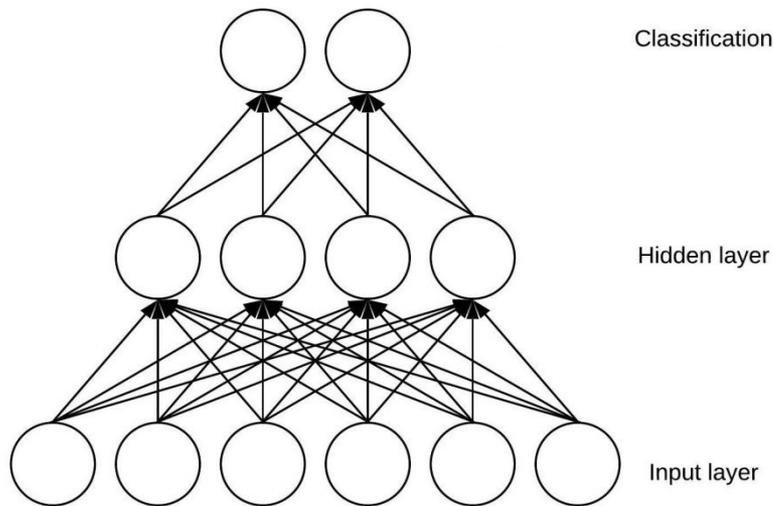
- Partly labeled Dataset
- Supervised teacher network
- „Trained“ student network
- Uncertainty measurement
- Teacher gets knowledge from student



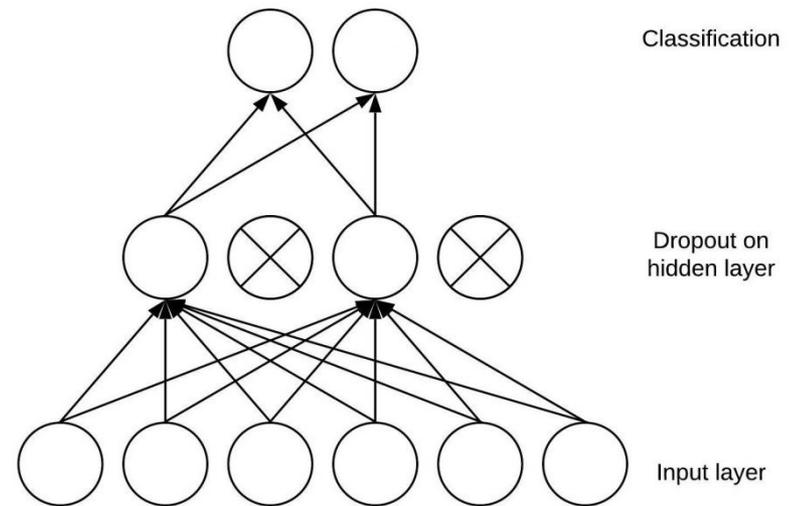
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# Dropout

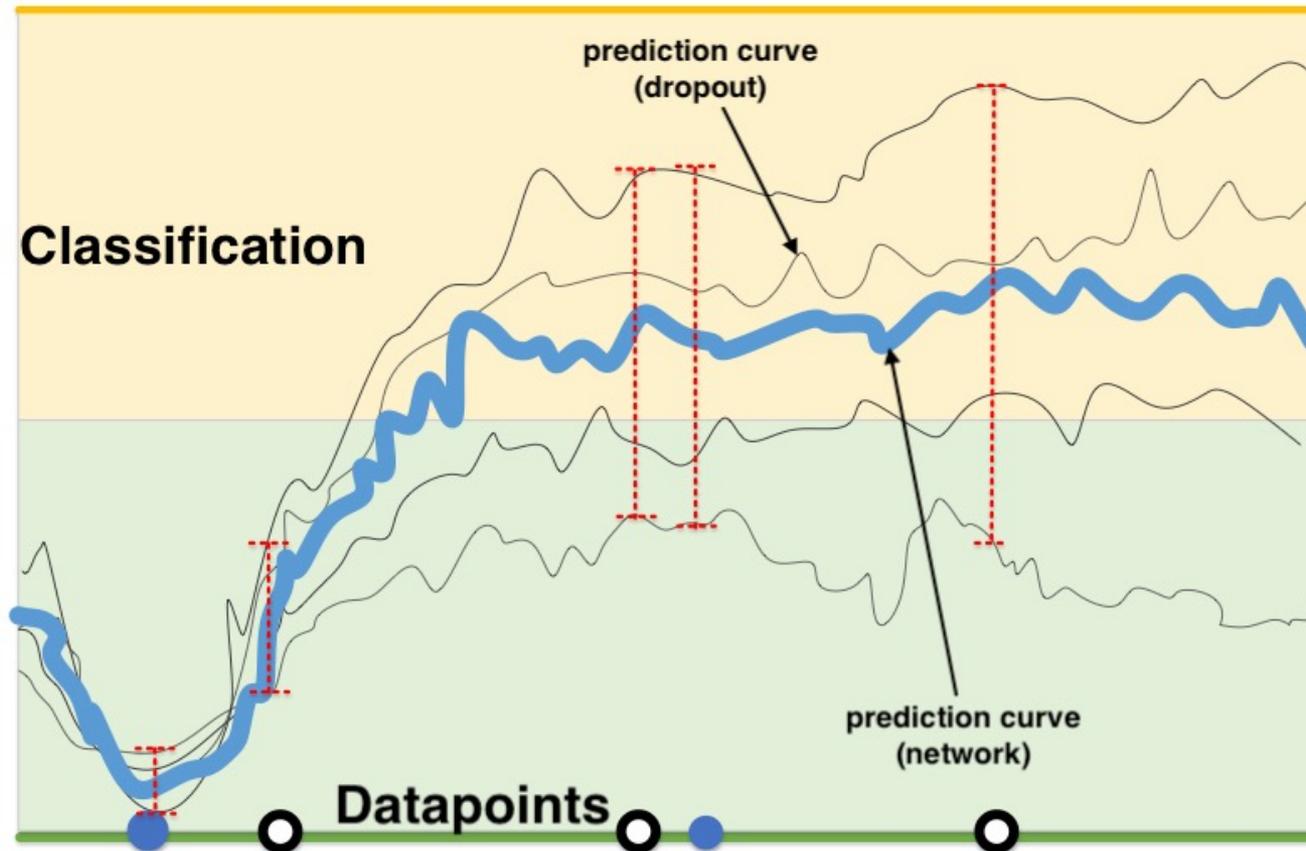


**Without Dropout**



**With Dropout**

# Dropout



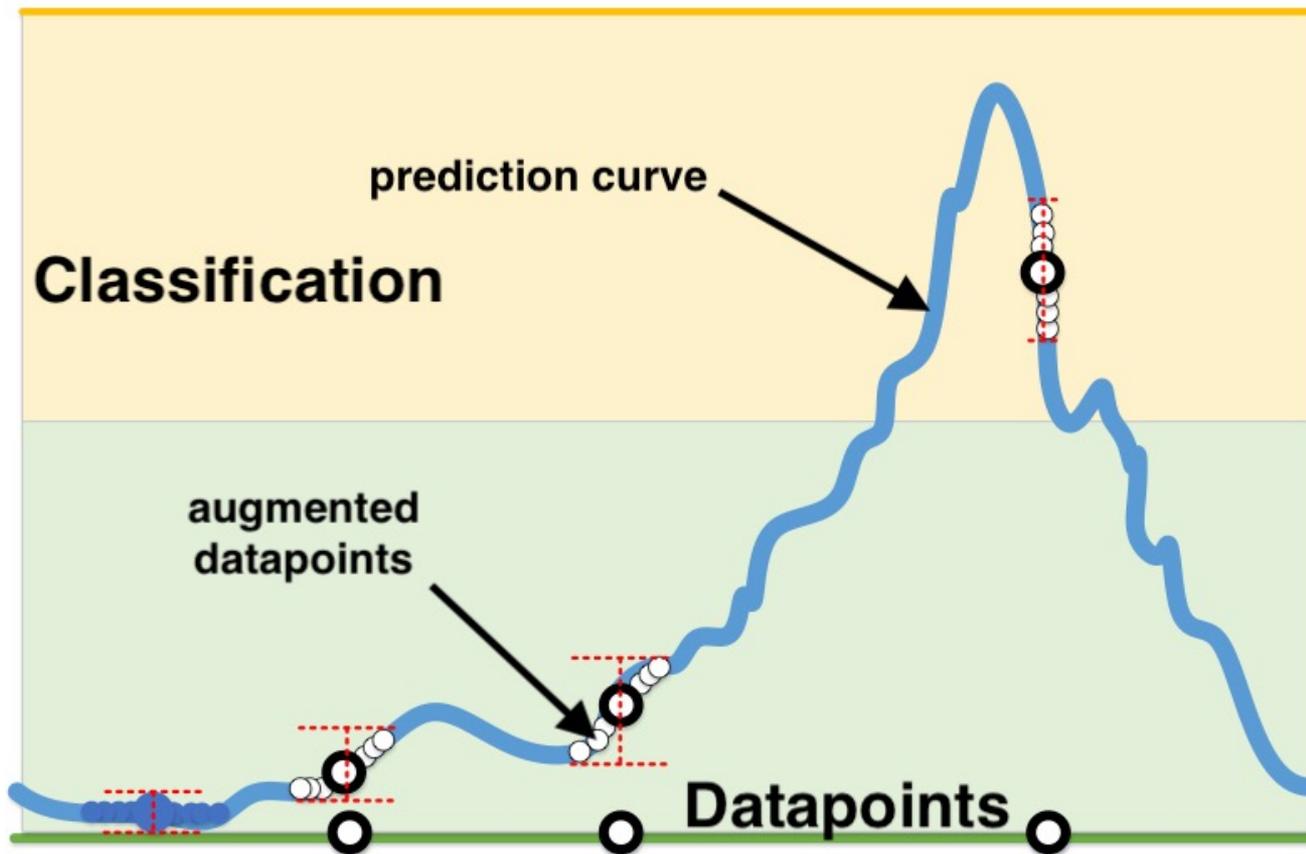
# Augmentation



**Image  
Augmentation**



# Augmentation



# Determine Uncertainty

Procedure:

1. Take batch B
2. Classify with teacher every  $x_i$  in B 20 times with dropout and augmentation
3. Calculate Criteria
4. Learn depending on the criteria

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- Measure variance over T times random samples
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e.g. Predictive Variance (PV):

- Variance of multiple soft predictions
- The larger the variance, the higher uncertainty

$$PV = \sum_c Var[p(y = c|x, \hat{\Theta}^1, \hat{\eta}^1), \dots, p(y = c|x, \hat{\Theta}^T, \hat{\eta}^T)]$$

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# Certainty-driven consistency with filtering

- Idea: Learn only from certain targets

# Certainty-driven consistency with filtering

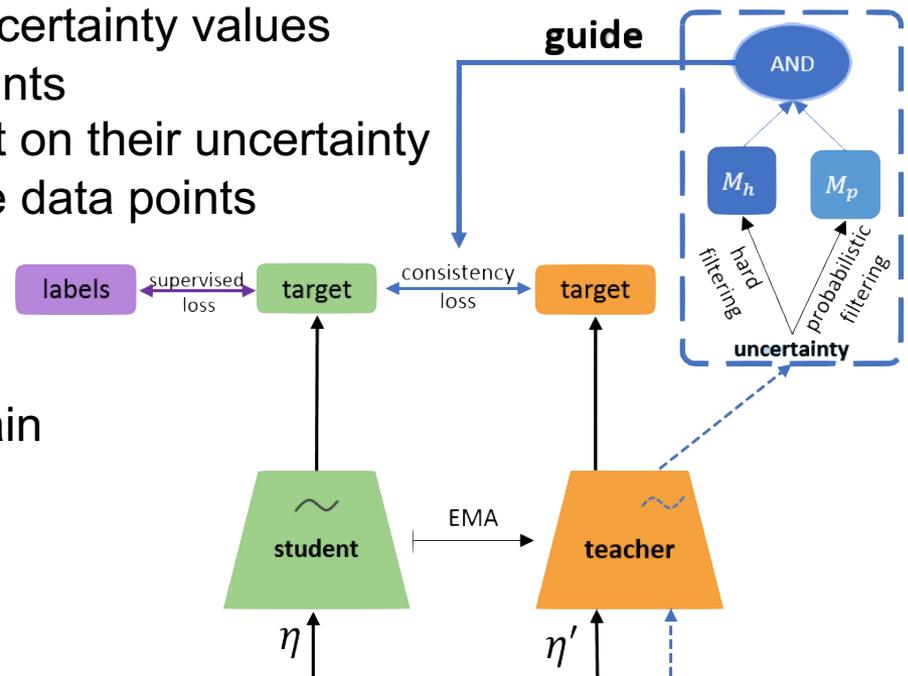
- Idea: Learn only from certain targets
- Procedure:
  1. Compute criteria for data points in input Batch  $B$
  2. Sort data points according to uncertainty values
  3. Chose the top- $k$  certain data points
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# Temperature CCL

- Idea: Learn more from certain targets and less from uncertain
  - „dark knowledge“ could be helpful
  - e.g. similarity between classes
- Procedure:
  - Use softmax activation with temperature

$$q_i = \frac{\exp(z_i/V_i)}{\sum_j \exp(z_j/V_j)}$$

- $V_i$  depends on certainty of  $x_i$
- If  $V_i = 1$ : softmax activation
- For large  $V_i$ : equal distribution

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# CIFAR

- 60.000 images
- CIFAR-10 and CIFAR-100

**airplane**



**automobile**



**bird**



**cat**



**deer**



**dog**



**frog**



**horse**



**ship**



**truck**



# SVHN

- Street View House Numbers Dataset
- 73.257 images

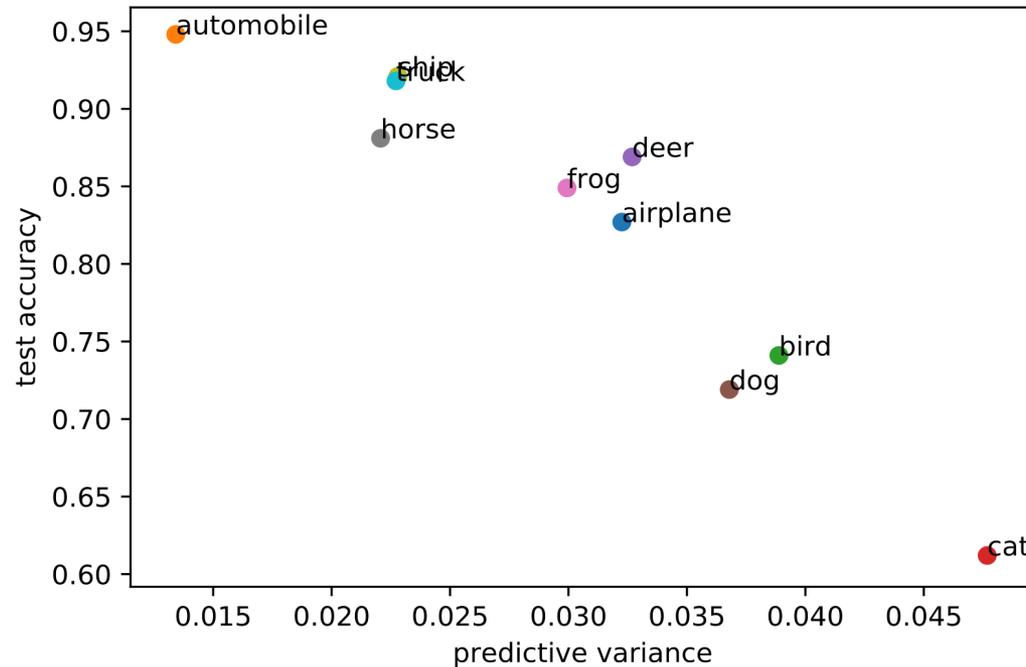


# Experiments overview

- Run every method 10 times (average)
- Metric: Error rate (%),  $\pm$  standard deviation

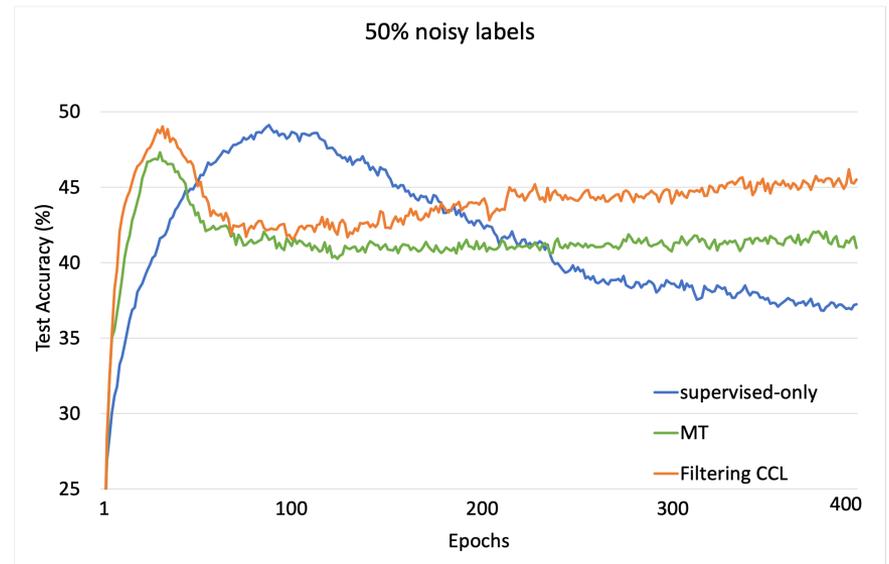
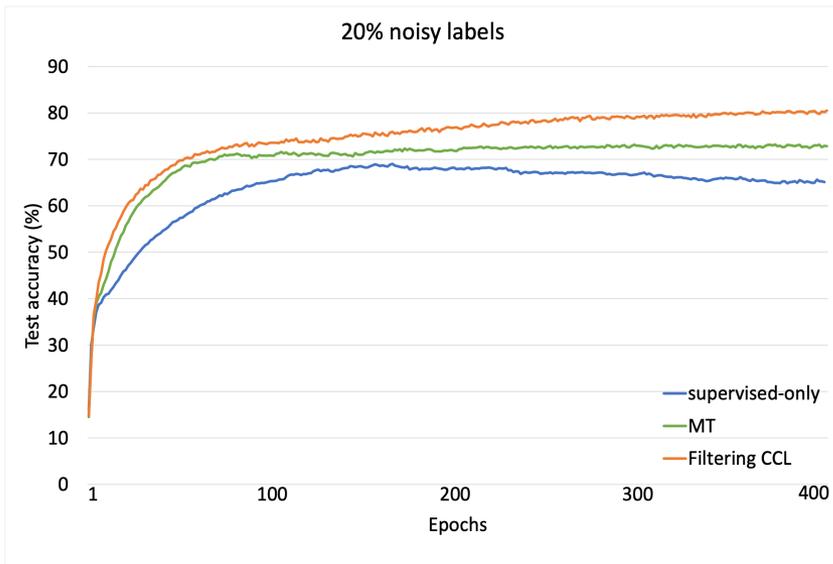
Model	CIFAR-10			SVHN	CIFAR-100
	1000 labels	2000 labels	4000 labels	1000 labels	10000 labels
Supervised-only	46.43 $\pm$ 1.21	33.94 $\pm$ 0.73	20.66 $\pm$ 0.57	12.32 $\pm$ 0.95	44.56 $\pm$ 0.30
$\Pi$ model	–	–	12.36 $\pm$ 0.31	4.82 $\pm$ 0.17	39.19 $\pm$ 0.36
TempEns	–	–	12.16 $\pm$ 0.24	4.42 $\pm$ 0.16	38.65 $\pm$ 0.51
VAT+Ent	–	–	10.55 $\pm$ 0.05	3.86 $\pm$ 0.11	–
MT	21.55 $\pm$ 1.48	15.73 $\pm$ 0.31	12.31 $\pm$ 0.28	3.95 $\pm$ 0.19	37.91 $\pm$ 0.37
$\Pi$ +SNTG	21.23 $\pm$ 1.27	14.65 $\pm$ 0.31	11.00 $\pm$ 0.13	<b>3.82 <math>\pm</math> 0.25</b>	37.97 $\pm$ 0.29
MT+SNTG	–	–	–	3.86 $\pm$ 0.27	–
TempEns+SNTG	18.41 $\pm$ 0.52	13.64 $\pm$ 0.32	10.93 $\pm$ 0.14	3.98 $\pm$ 0.21	–
MA-DNN	–	–	11.91 $\pm$ 0.22	4.21 $\pm$ 0.12	<b>34.51 <math>\pm</math> 0.61</b>
Filtering CCL ( <b>ours</b> )	<b>16.99 <math>\pm</math> 0.71</b>	12.57 $\pm$ 0.47	<b>10.63 <math>\pm</math> 0.22</b>	3.86 $\pm$ 0.19	34.81 $\pm$ 0.52
Temperature CCL ( <b>ours</b> )	17.26 $\pm$ 0.69	<b>12.45 <math>\pm</math> 0.33</b>	10.73 $\pm$ 0.26	3.93 $\pm$ 0.21	35.15 $\pm$ 0.62

# Accuracy vs. PV



- Measurement of PV and accuracy in the CIFAR data set
- Inverse relationship between class accuracy and predictive variance

# Robustness to noisy labels



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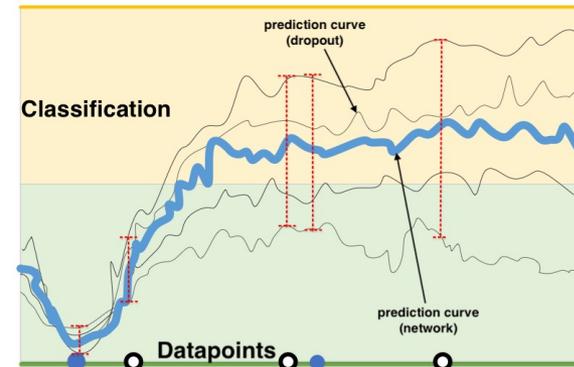
- Semi-supervised Learning
  - Labeling is expensive
  - Learn from partly labeled data set

# Sum up

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- Only learn from certain data points

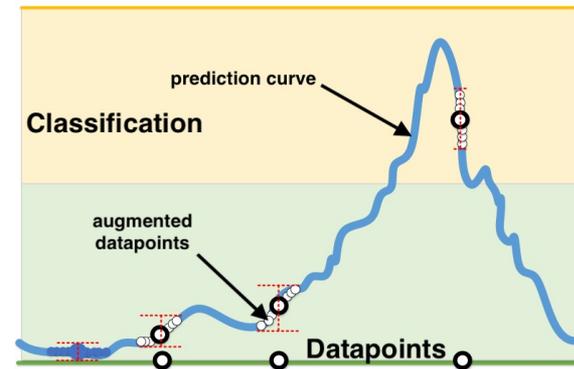
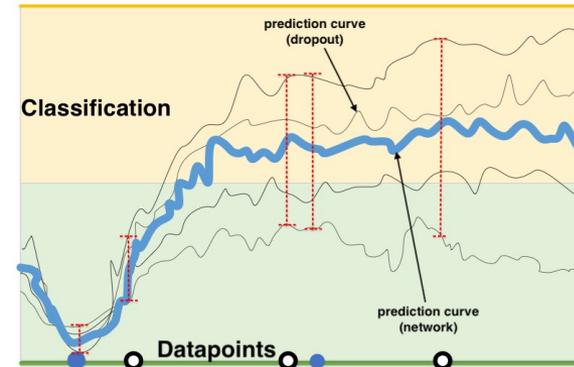
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- Determine uncertainty with dropout



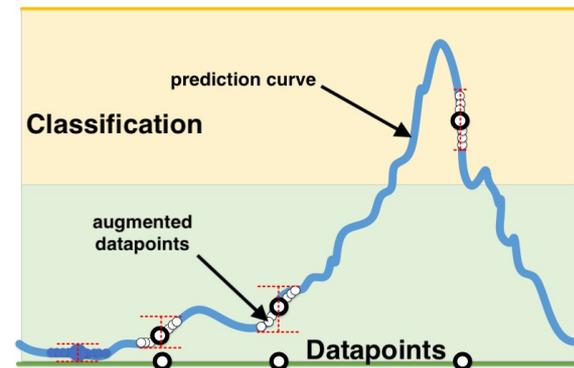
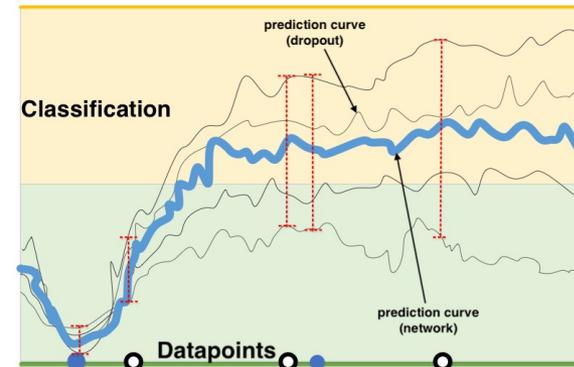
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- Semi-supervised Learning
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  - Learn from partly labeled data set
- Only learn from certain data points
- Determine uncertainty with dropout and augmentation
  - Classify one data point multiple times with random dropout and augmentation
  - Compute criteria and get uncertainty



# Sum up

- Semi-supervised Learning
  - Labeling is expensive
  - Learn from partly labeled data set
- Only learn from certain data points
- Determine uncertainty with dropout and augmentation
  - Classify one data point multiple times with random dropout and augmentation
  - Compute criteria and get uncertainty
- Use filtering or temperature to learn from certain data points

