RUB

RUHR-UNIVERSITÄT BOCHUM

UNCERTAINTY ESTIMATION IN FEDERATED DEEP LEARNING

Florian Linsner

Table of Contents

Chapter
Mathematical Basics

Entropy and Variance

- Shannon Entropy over output classes

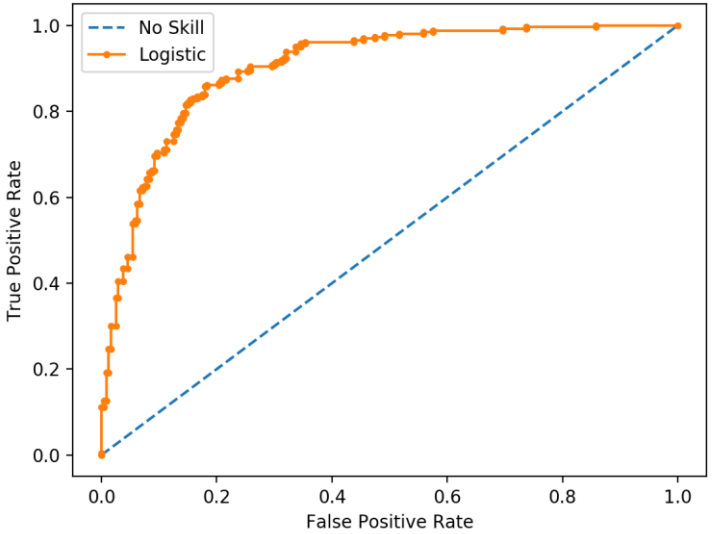
$$H\left(p\left(Y|x^*,\theta\right)\right) = -\sum_{k=1}^{K} p\left(y_k|x^*,\theta\right) \cdot \log p\left(y_k|x^*,\theta\right)$$

- Variance over multiple predictions for a fixed input

$$\sigma^2 = \frac{1}{S}\sum_{s=1}^{S} p\left(y|x^*,\theta_s\right)^2 - p\left(y|x^*\right)^2$$

ROC and AUROC

- Receiver Operating Characterisitc Curve
  - Binary classifier
  - 2 groups of data
  - True Positive vs False Positive
  - Multiple Theshholds
- Area Under ROC
  - Score between 0.5 and 1
  - Want to achieve a score of 1



Uncertainty Estimation in Federated Deep Learning
Image: https://machinelearningmastery.com/

Chapter
Uncertainty Theorie

Importance of Uncertainty

- We use models to make predictions
  - Can we trust these predictions?
- There is no perfect model
  - No-Free-Lunch-Theorem
  - Models make mistakes!
- Many Decisions in critical environments
  - Autonomous Driving
  - Nuclear Powerplants
  - Industrial Settings

Malicious Intentions

- An Attacker can Influence the beaviour of a model
- Data Poisoning
- Aversarial Examples
- Many other

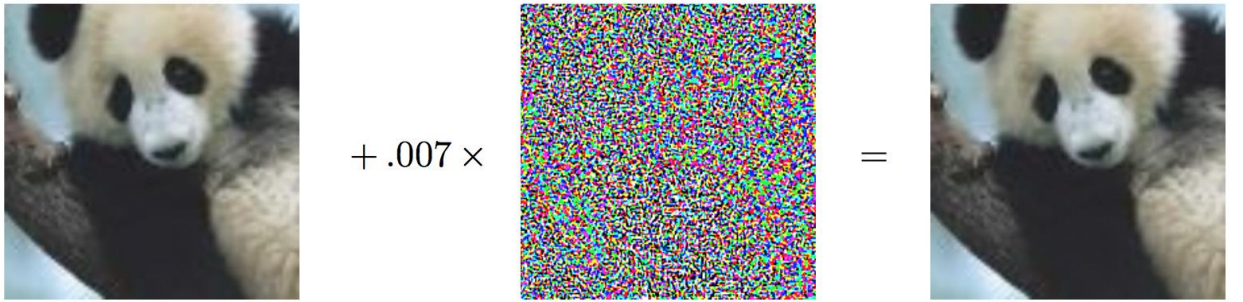


Image: https://pytorch.org/tutorials/_images/fgsm_panda_image.png

Bayesian Uncertainty - Origins

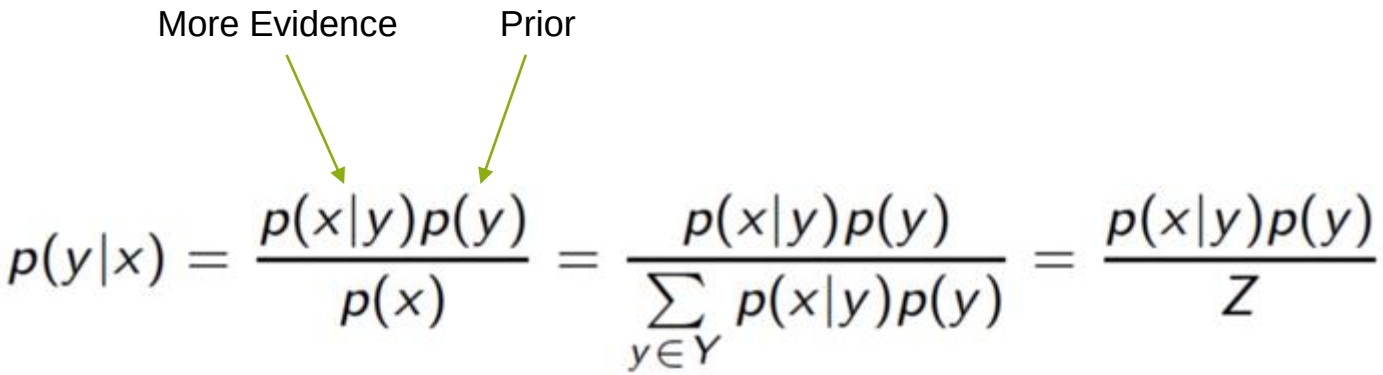
$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} = \frac{p(x|y)p(y)}{\sum_{y \in Y} p(x|y)p(y)} = \frac{p(x|y)p(y)}{Z}$$

Bayesian Uncertainty - Origins

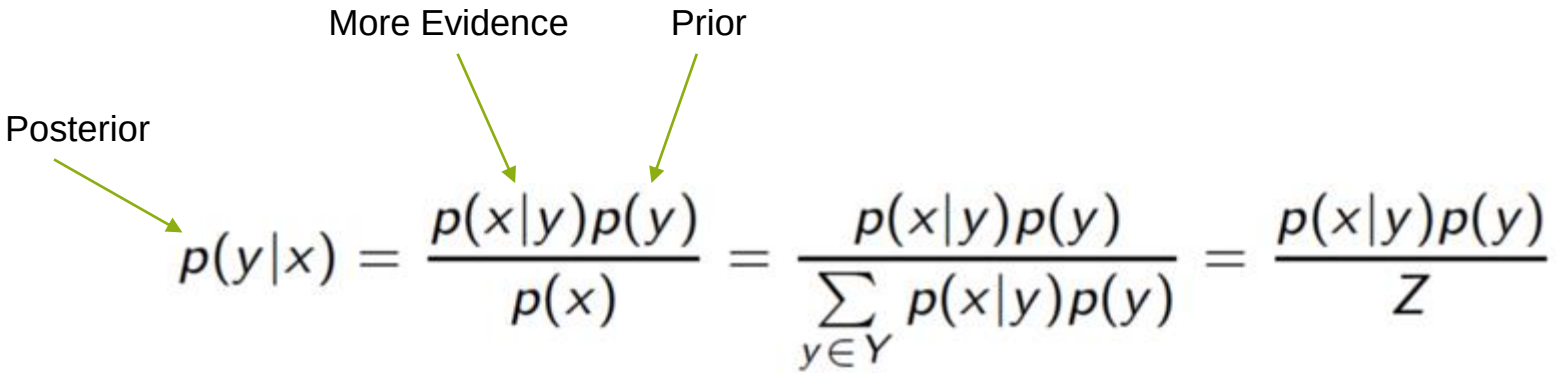
Prior

$$p(y|x) = \frac{p(x|y)p(y)}{p(x)} = \frac{p(x|y)p(y)}{\sum_{y \in Y} p(x|y)p(y)} = \frac{p(x|y)p(y)}{Z}$$

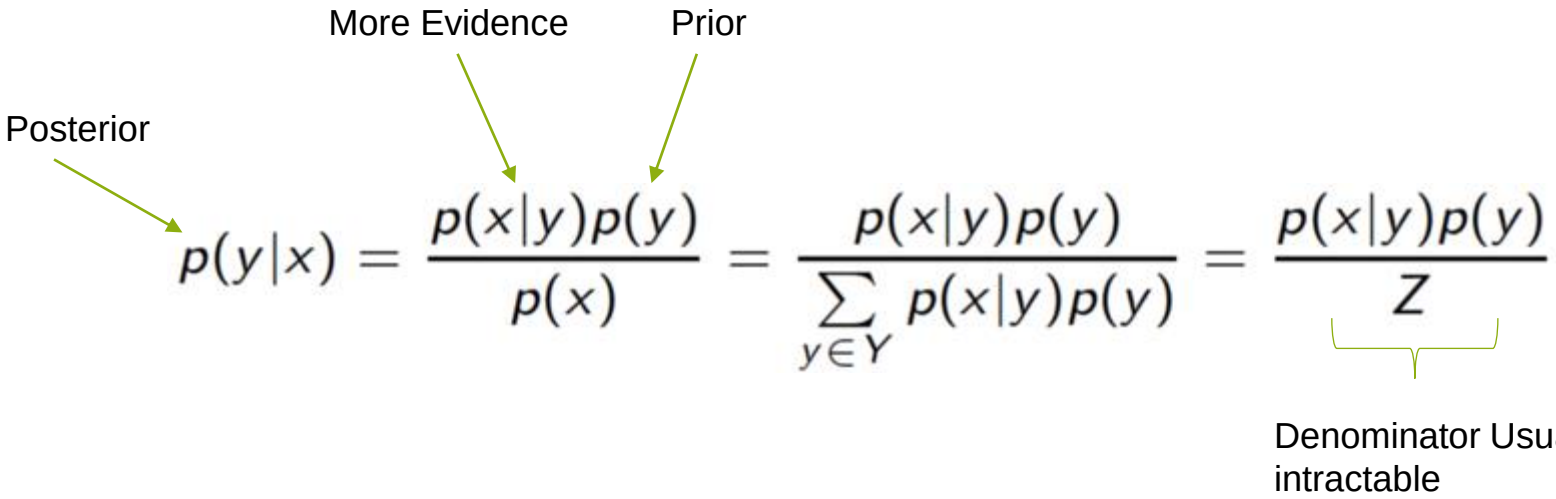
Bayesian Uncertainty - Origins



Bayesian Uncertainty - Origins



Bayesian Uncertainty - Origins



Bayesian Uncertainty - Usage

- Stating priors over model parameters β
- Using training data (X, y)

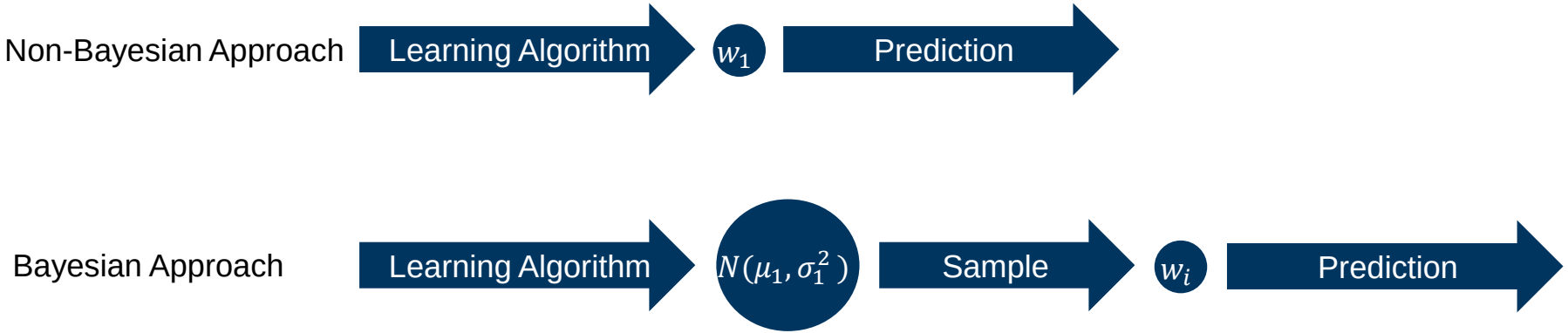
Bayesian Uncertainty - Usage

- Stating priors over model parameters β
- Using training data (X, y)

$$p(\beta|y_t, X_t) = \frac{p(y_t, X_t|\beta)p(\beta)}{p(y_t, X_t)} = \frac{p(y_t, X_t|\beta)p(\beta)}{\int p(y_t, X_t|\beta)p(\beta)d\beta}$$

- Solving analytically is often impossible/impractical
- Solution: Numeric Approximations

Bayesian Uncertainty - Usage

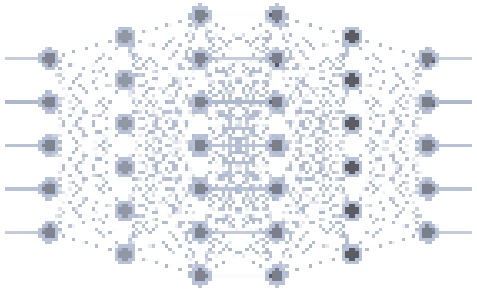


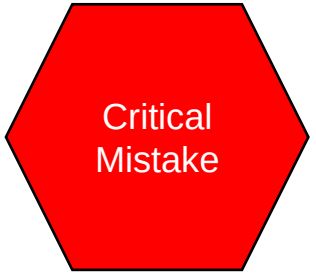
Chapter

Methods for Uncertainty

Ensembles

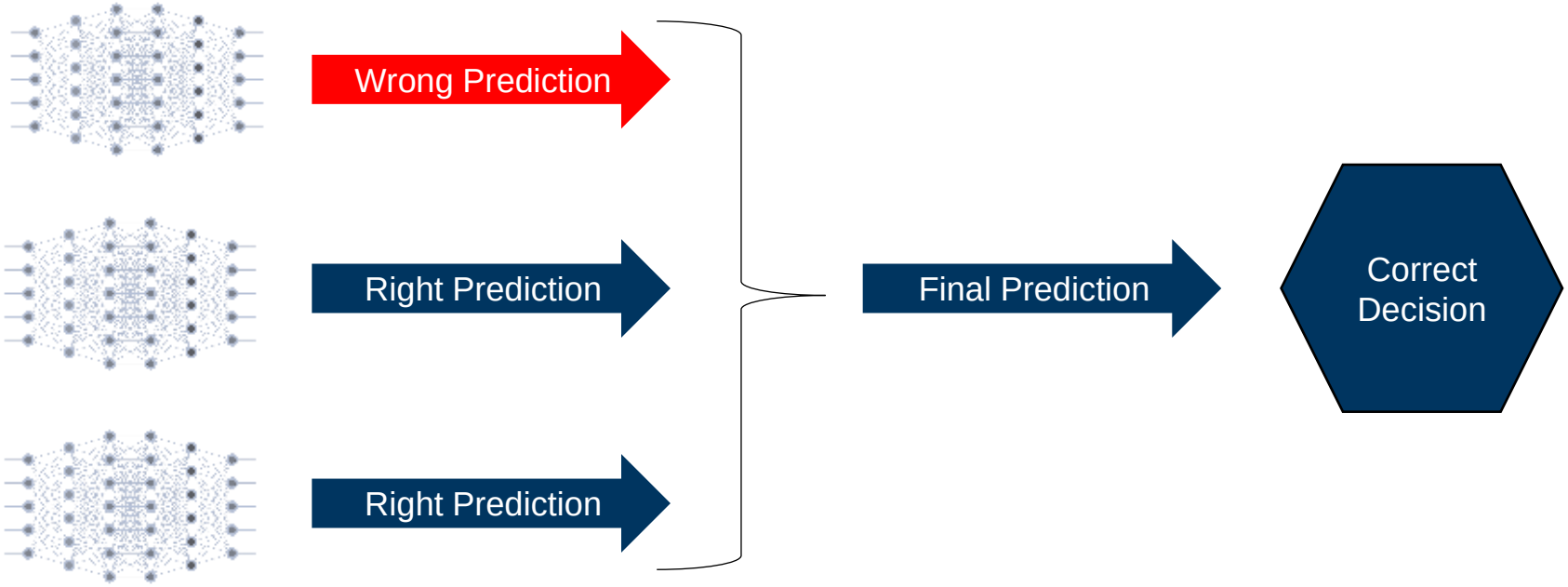
- Originally proposed as non-Bayesian method
- Can be viewed as Bayesian Approximation[1]



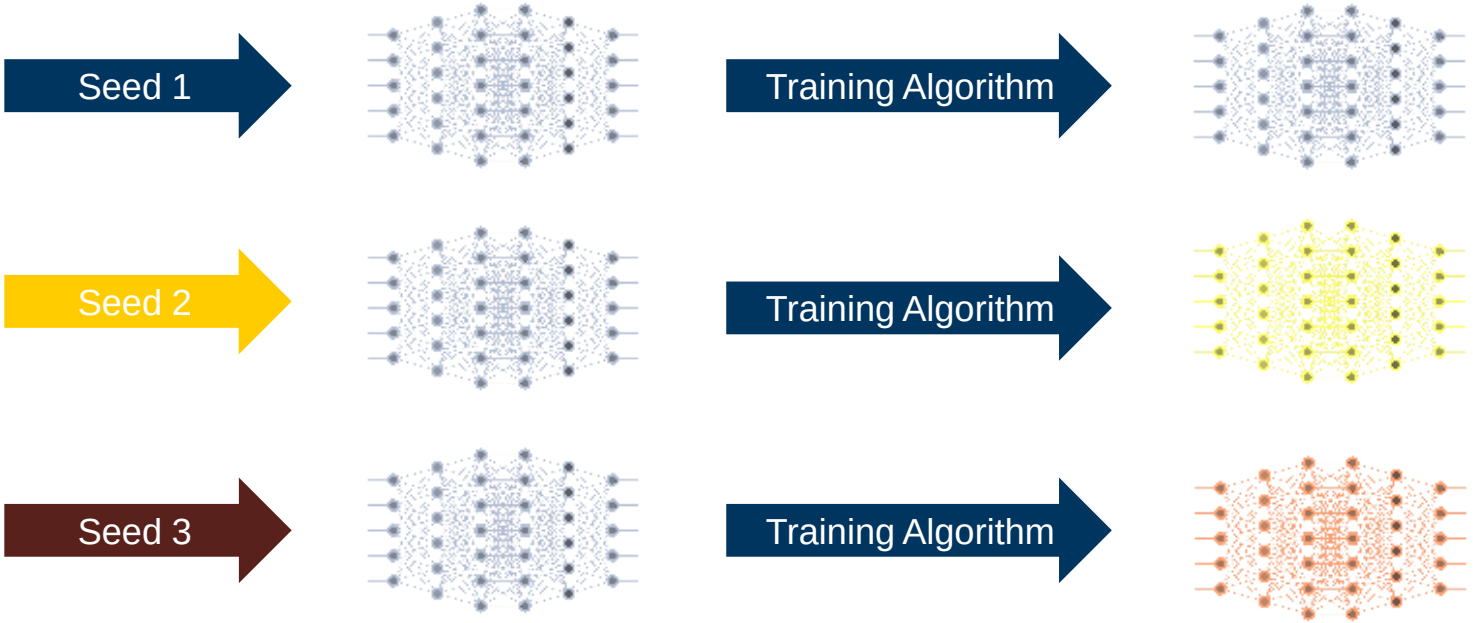


[1]Hoffman et. Al. Deep Ensembles from a Bayesian Perspectiv

Ensembles

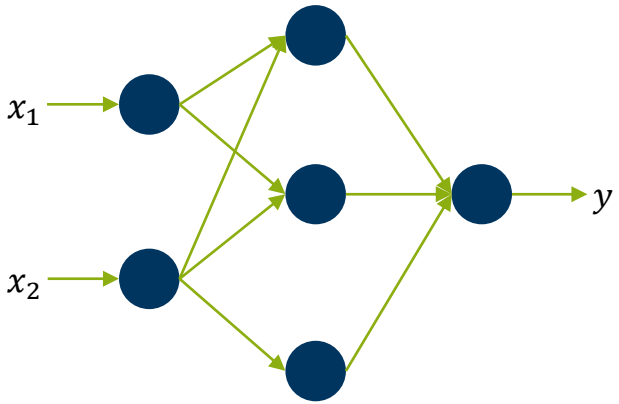

Wrong Prediction
Right Prediction
Right Prediction
Final Prediction
Correct Decision

Ensemble Training



Dropout

- Method for Regularization during Training Time
- Prevents Overfitting

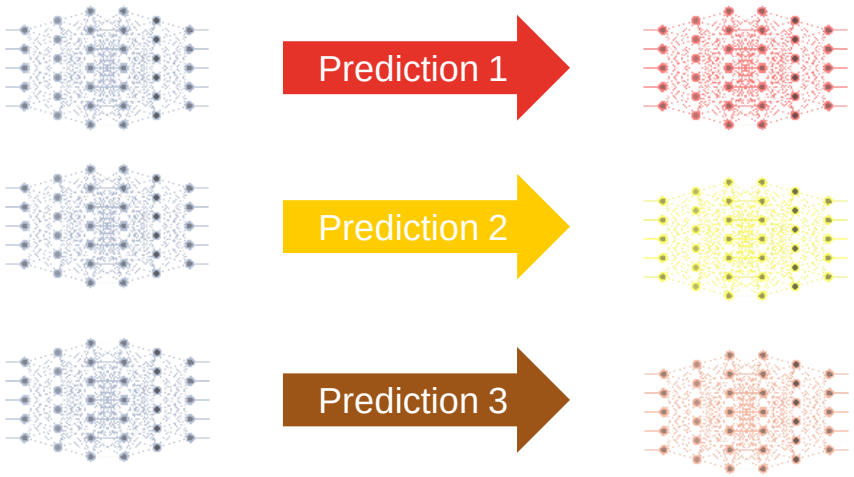


Dropout

- Method for Regularization during Training Time
- Prevents Overfitting

MC-Dropout

- MC-Dropout as Bayesian Approximation[2]
- Dropout During Prediction Time
- Multiple Predictions for same Input



Uncertainty Estimation in Federated Deep Learning

[2] Gal et. Al. Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning

SWAG

- Stochastic Weight Averaging Gaussian[3]
- Needs Pre-Trained Solution near a local minima
- Compute a running average

$$\theta_{\text{SWA}} = \frac{1}{T}\sum_{i=1}^{T}\theta_i$$

- Compute squared running average

$$\overline{\theta^2} = \frac{1}{T}\sum_{i=1}^{T}\theta_i^2$$

[3]Maddox et. Al. A Simple Baseline for Bayesian Uncertainty in Deep Learning

SWAG

- Compute Covariance

$$\Sigma_{\text{diag}} = \text{diag}(\overline{\theta^2} - \theta^2_{\text{SWA}})$$

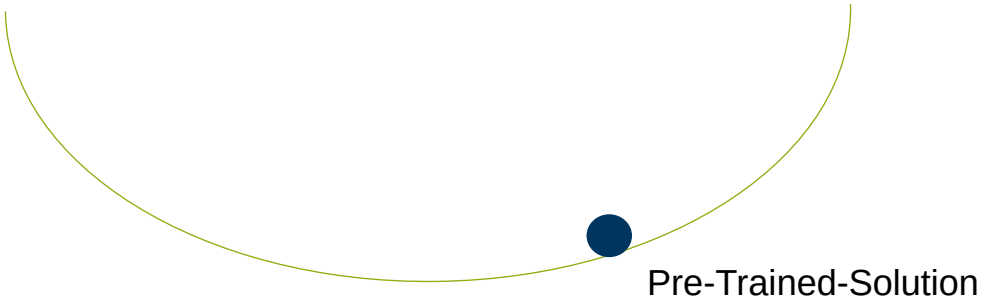
- Sample from Distribution

$$\mathcal{N}(\theta_{\text{SWA}}, \Sigma_{\text{Diag}})$$

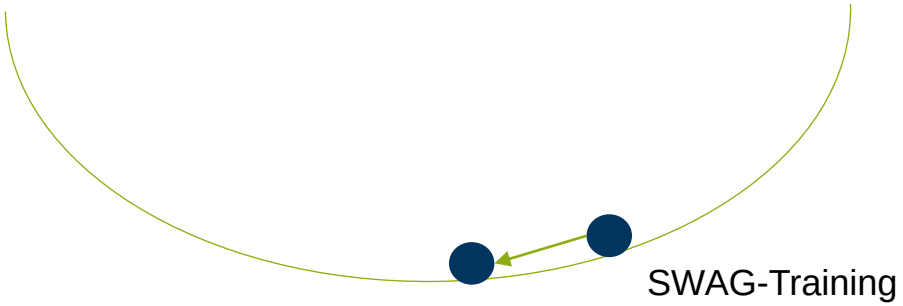
SWAG in Pictures

Loss-Surface

SWAG in Pictures

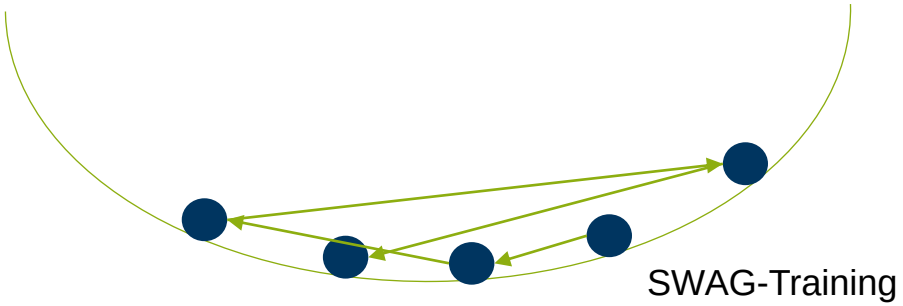


SWAG in Pictures



SWAG in Pictures

- Goal: More Centered Solution



SWAG in Pictures

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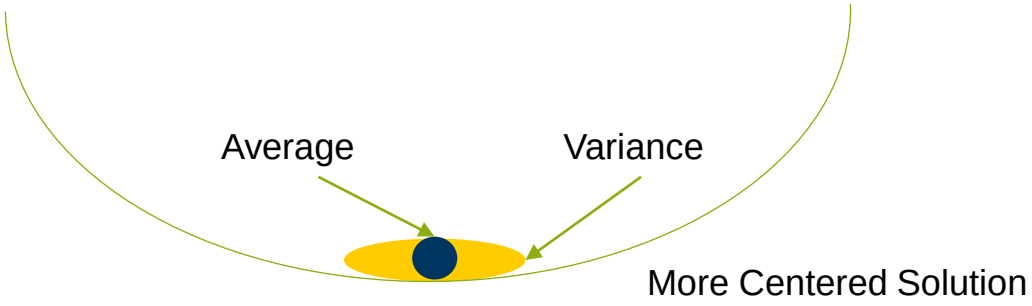

Chapter

Challenges in Centralized Deep Learning

Data Generating Devices

- $50.1 \cdot 10^9$connected devices by 2020[4]
  - (autonomous) driving and vehicles
  - Smart sensors
  - Mobile phones
  - Airplanes
  - Entertainment Devices
  - Industrial Machines
  - …
- IoT sector is growing exponentially

[4] Nitinder Mohan and Jussi Kangasharju. *Edge-fog cloud: A distributed cloud for internet of things computations*. In Cloudification of the Internet of Things (CIoT), pages 1–6. IEEE, 2016.

Centralized Machine Learning

Uncertainty Estimation in Federated Deep Learning

Image: https://d1.awsstatic.com/what-is-aws/AWS-Types-of-Cloud-Computing_Infrastructure-as-a-Service.c2e061a42b68ec6d969880fb8768bcb8e5cc2e69.png

Centralized Machine Learning

Uncertainty Estimation in Federated Deep Learning
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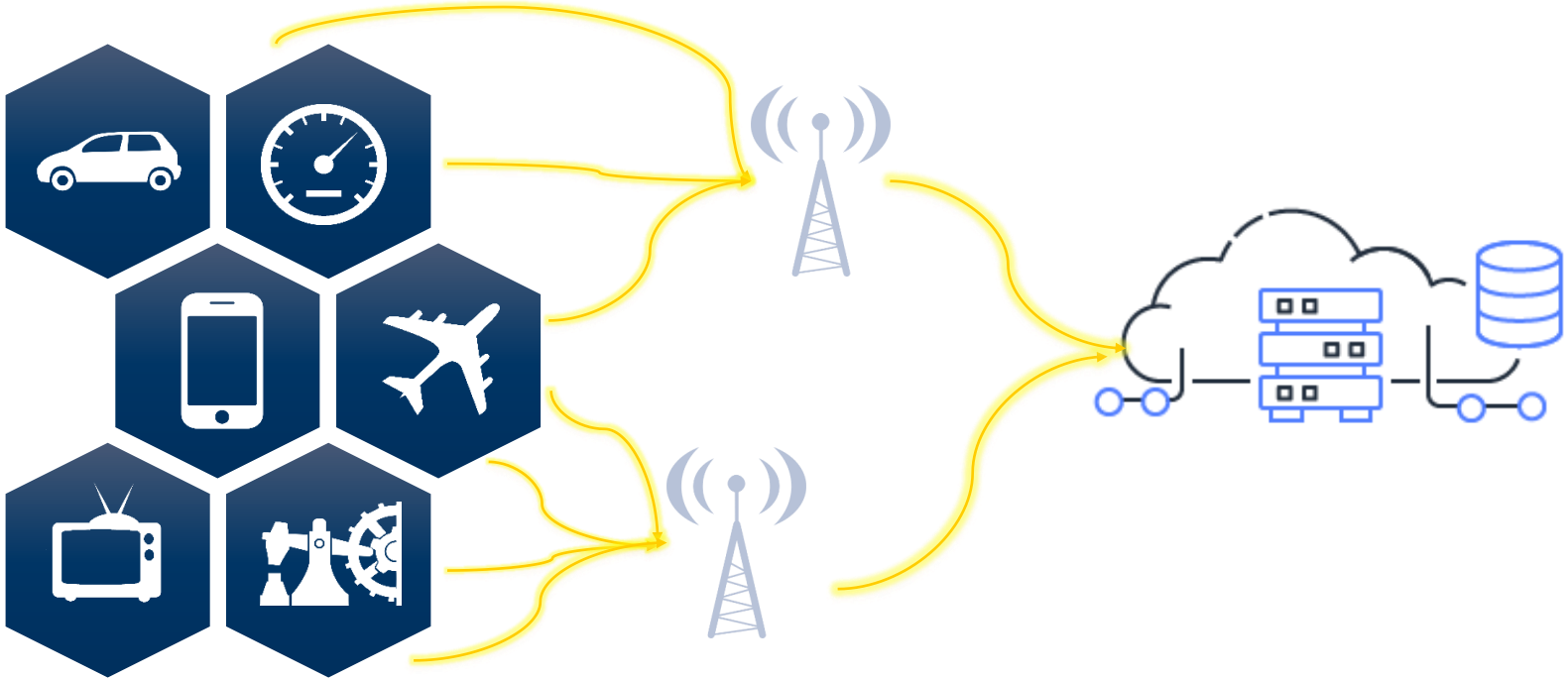
Centralized Machine Learning



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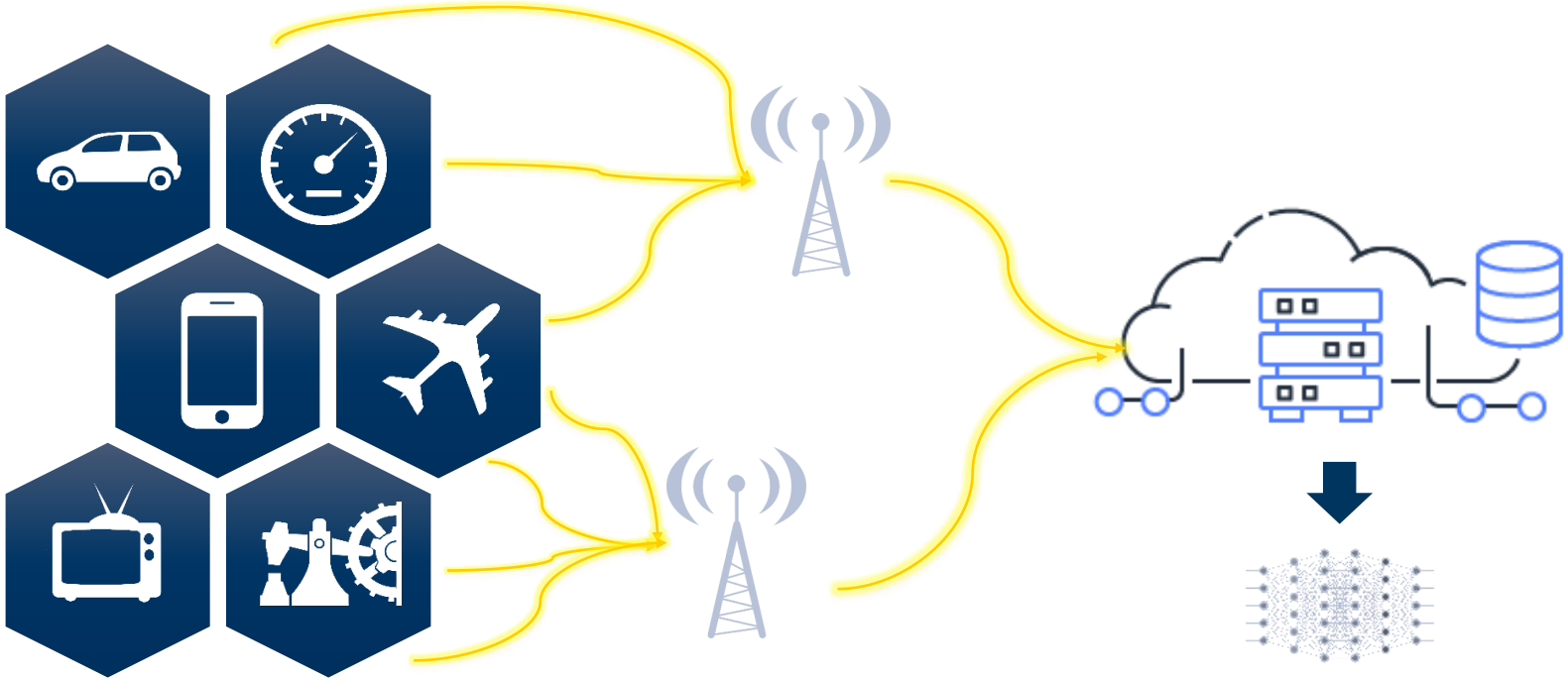
Centralized Machine Learning



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Limits of Cloud Processing

- Autonomous vehicle generates 1GB per second[5]
  - 4G mobile: 37.5 MB per second
  - VW sold $10.8 \cdot 10^6$ cars in 2018
  - Produce 10.3 PB data per second
  - All CERN experiments process 25 GB per second[6]

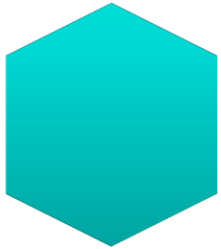
Uncertainty Estimation in Federated Deep Learning
[5]Shi, Weisong et al. *Edge computing: Vision and challenges*. Internet of Things Journal, pages 637–646. IEEE, 2016
[6]CERN: Processing: What to record? (URL: https://home.cern/science/computing/processing-what-record), retrieved 27.3.2019.

Limits of Cloud Processing

- Siemens collects 2EB data per day[7]
  - Sensor data can reveal corporate secrets (e.g., machine settings)
  - Predictive maintenance models usually trained on all data[8]

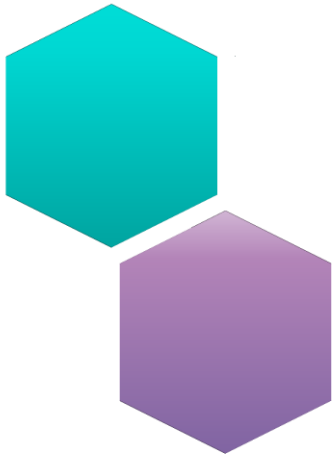
[7]Rüdiger Köhn. *Ringen um die Vorherrschaft über Industrie 4.0*. Blick in die Zukunft: Trends und Szenarien für die Welt von morgen. FAZ, 2014.
[8] Lee, Jay, Hung-An Kao, and Shanhu Yang. *Service innovation and smart analytics for industry 4.0 and big data environment*. In CIRP, pages 3-8, 2014.

Centralized Learning Approach



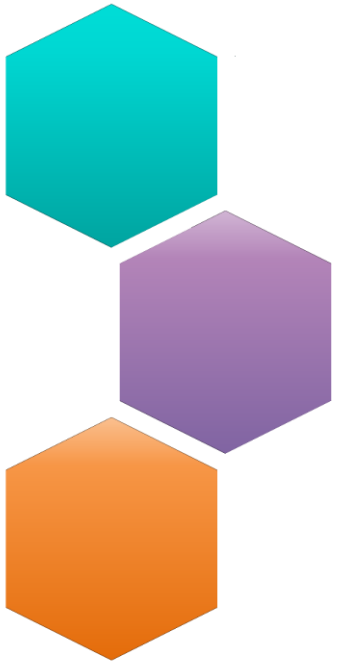
- does not scale with number of devices and neglects their computing power

Centralized Learning Approach



- does not scale with number of devices and neglects their computing power
- prohibitive communication costs

Centralized Learning Approach



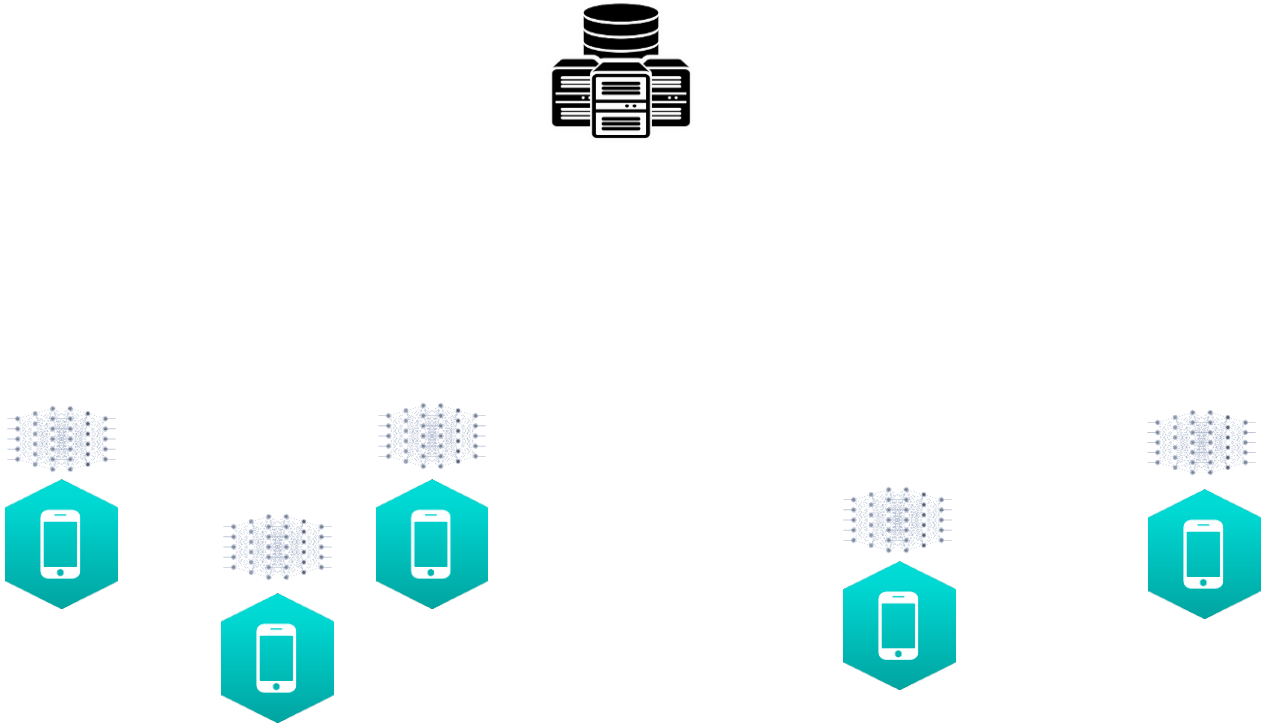
- does not scale with number of devices and neglects their computing power
- prohibitive communication costs
- requires sharing of privacy-sensitive data

Chapter
Federated Deep Learning

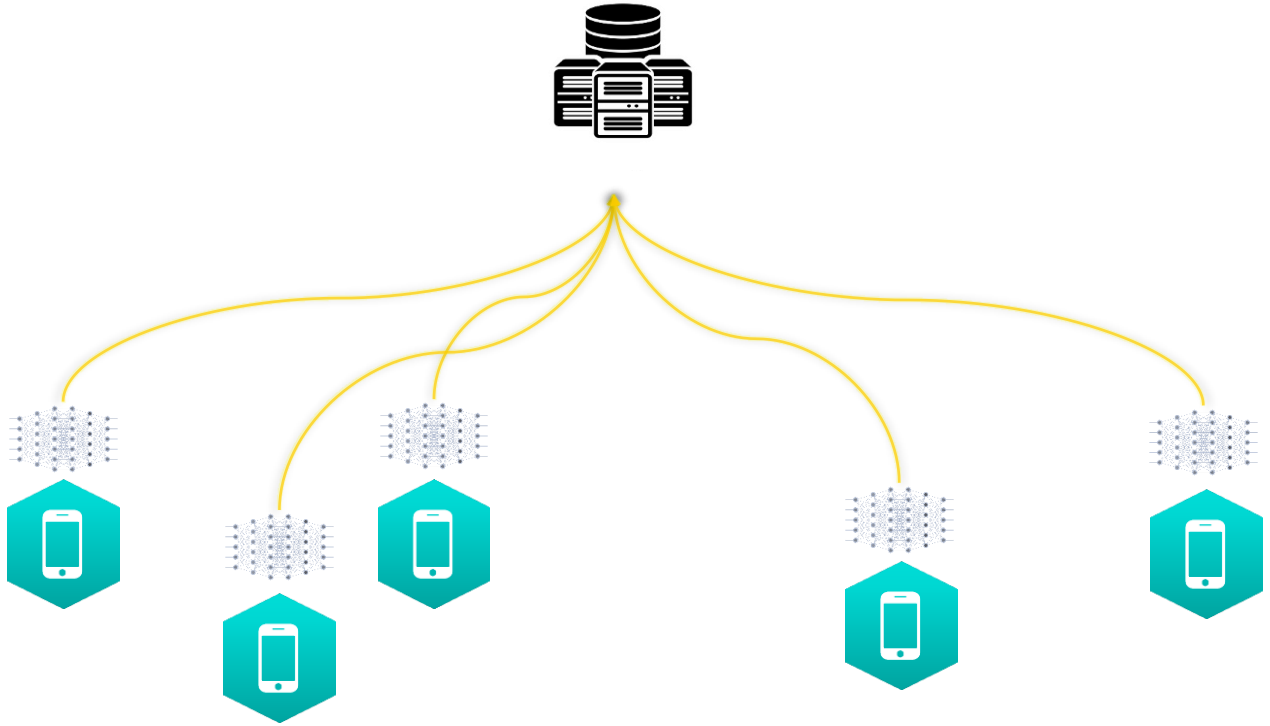
Federated Deep Learning Approach

Federated Deep Learning Approach

Federated Deep Learning Approach



Federated Deep Learning Approach



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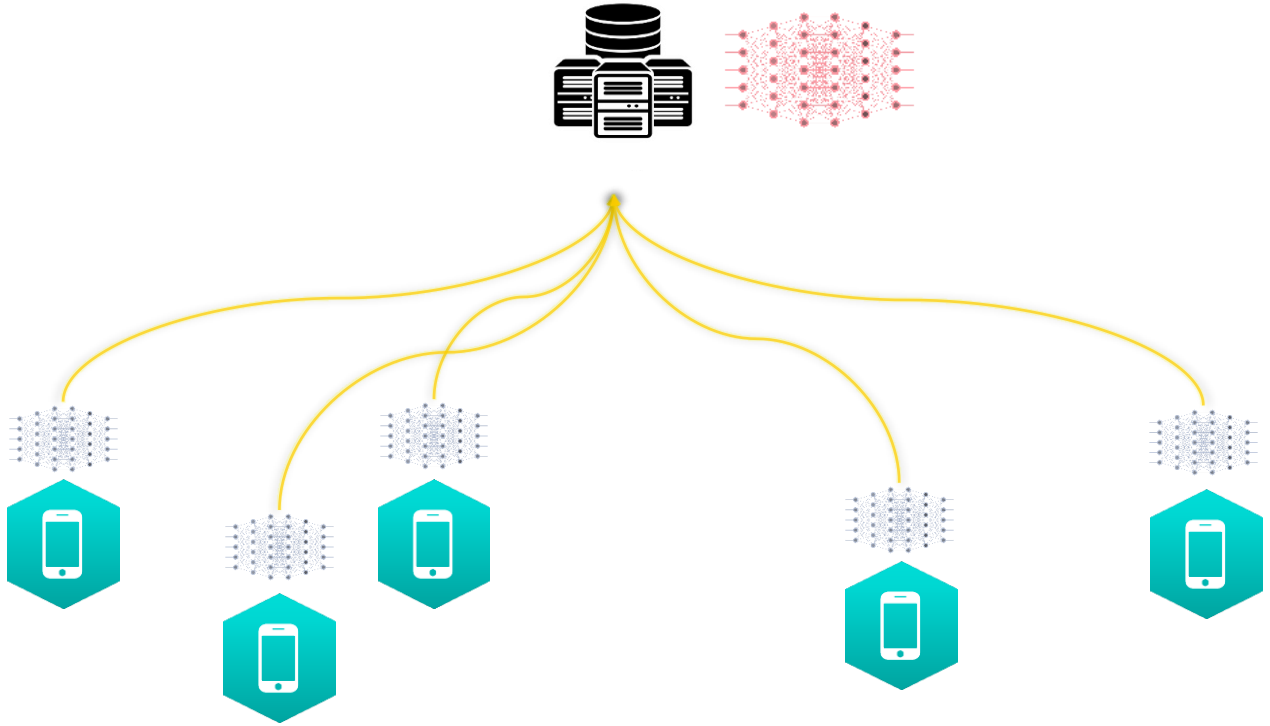

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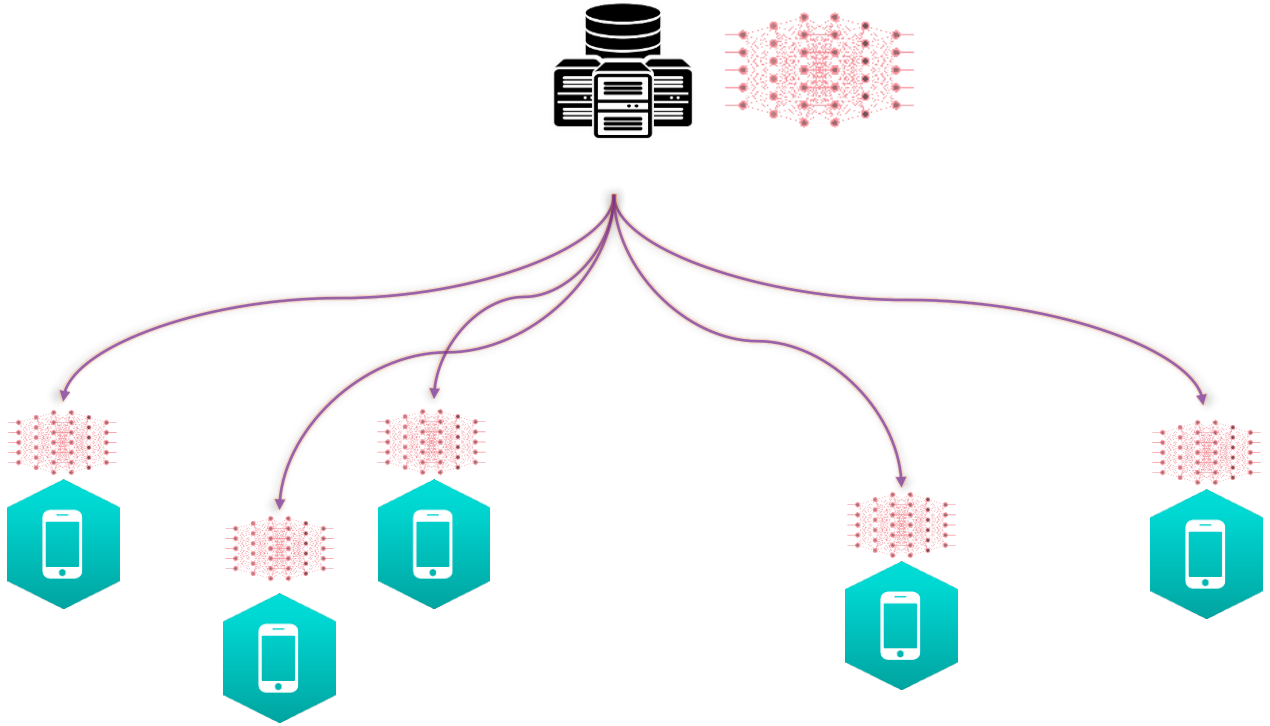
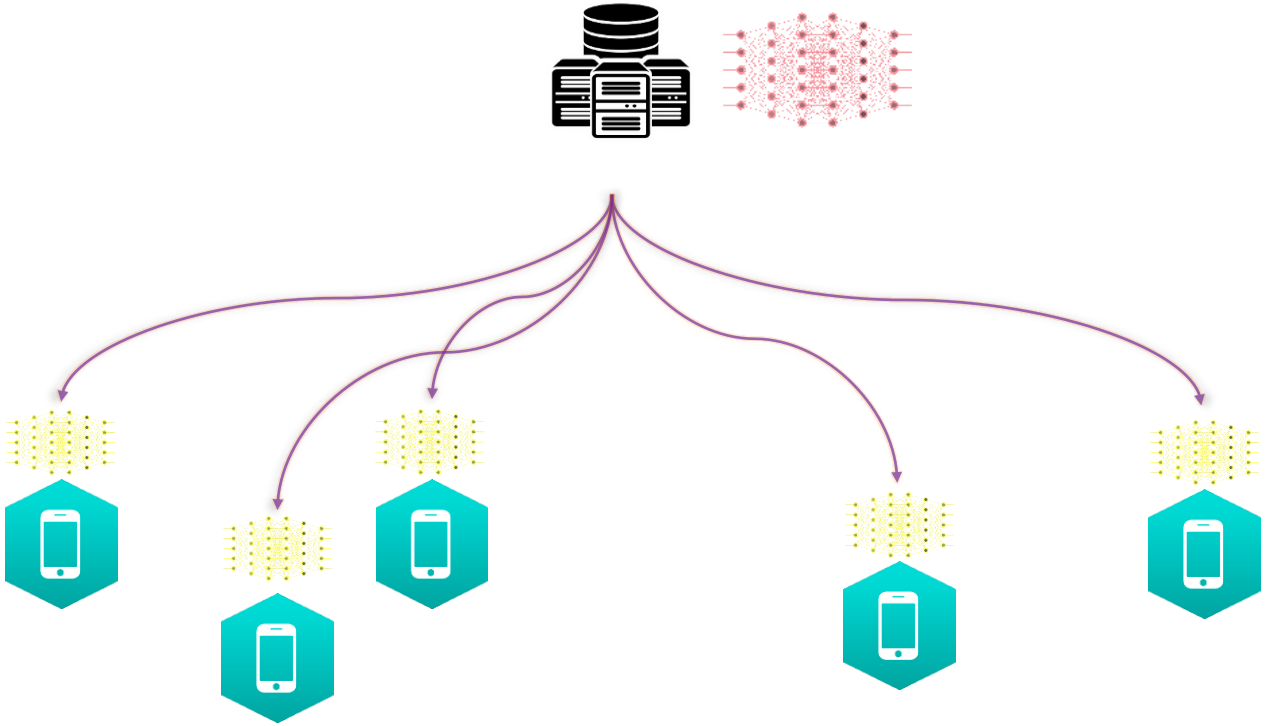
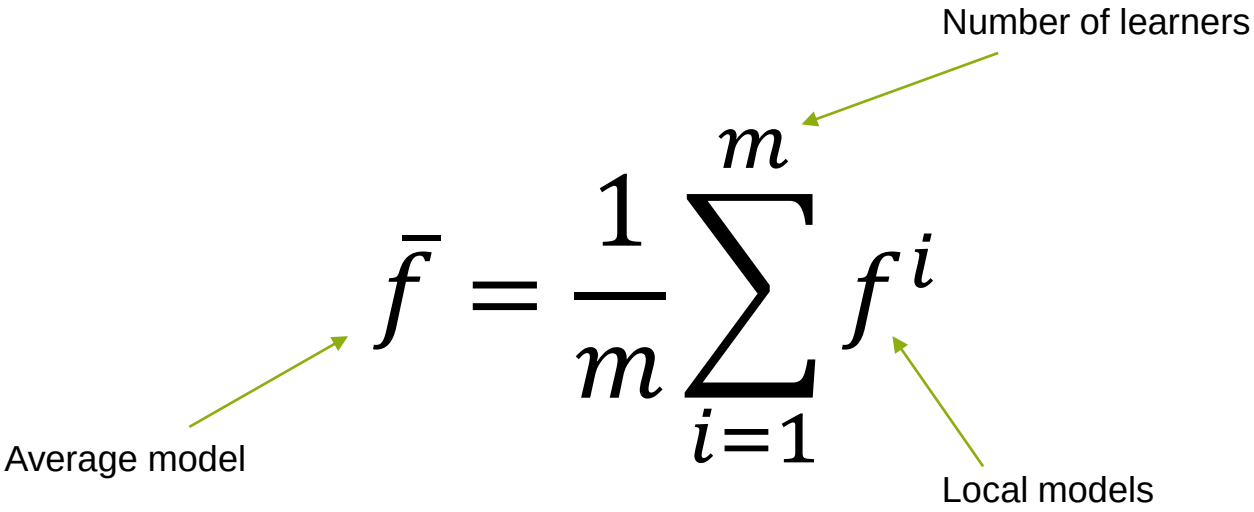


Federated Deep Learning Approach



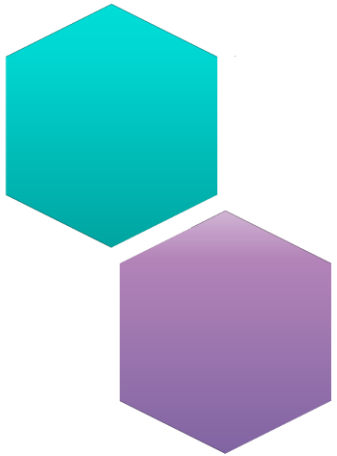
Model Aggregation



Properties

- independent of the learning algorithm (black-box)

Properties



- independent of the learning algorithm (black-box)
- works for large amount of model classes (linear + kernel models, various DNNs)

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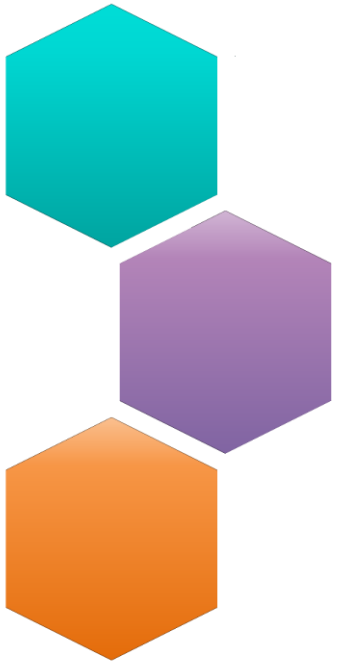

- independent of the learning algorithm (black-box)
- works for large amount of model classes (linear + kernel models, various DNNs)
- requires that models can be trained locally, e.g., sufficient local computing power, and labels available

Requirements

1. The Model trained in parallel has a high quality similar to one obtained by a the serial application of the learning algorithm.

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Privacy

- Additional inherent Feature
  - No Data is Shared between Parties
  - Only Model Weights are Shared
- Can be proven to be *differential private*[9]
  - By clipping the Gradient for each Weight

[9]Rodriguez-Barroso et. Al. Federated Learning and Differential Privacy: Software tools analysis, the Sherpa.ai FL framework and methodological guidelines for preserving data privacy

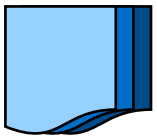
Chapter

Leveraging Uncertainty in Federated Deep Learning

Notation

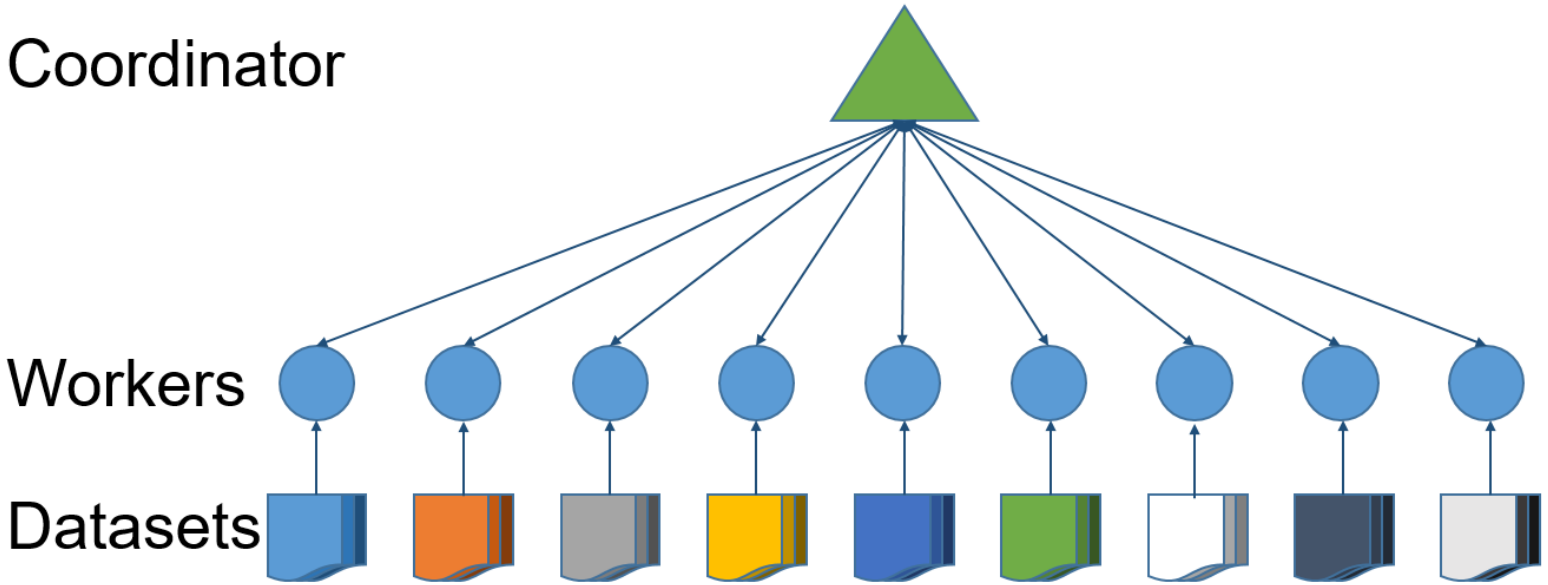
- Communicator: Averages Models

- Worker: Trains Models

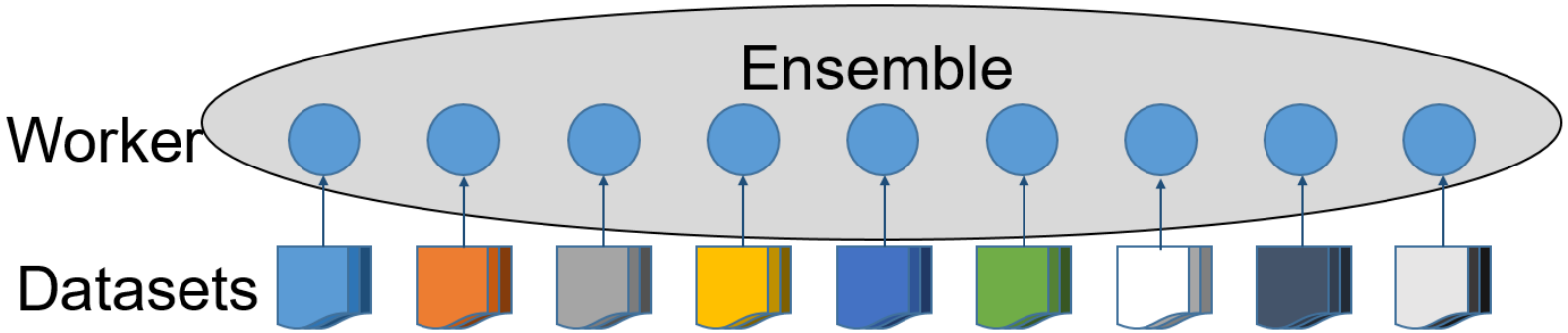


- Dataset: Contains Private Data

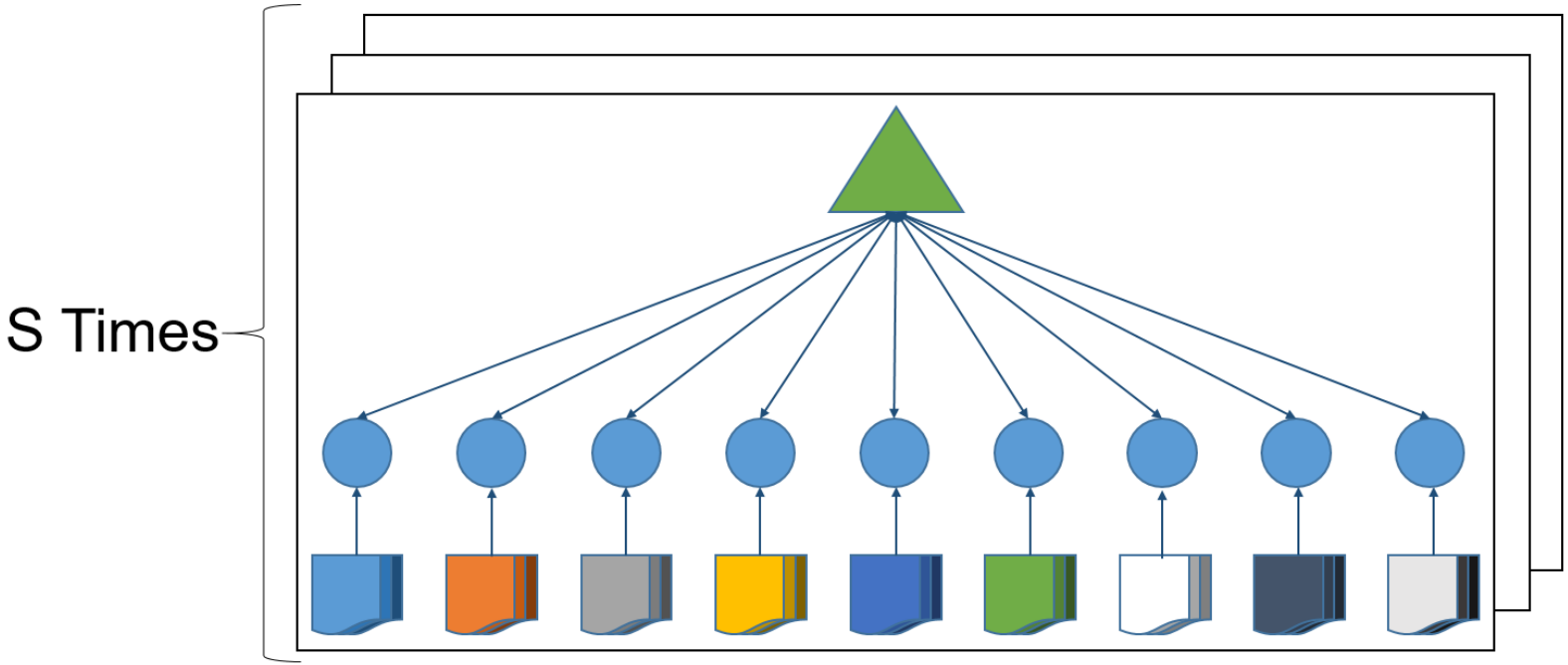
Global Model (Baseline)



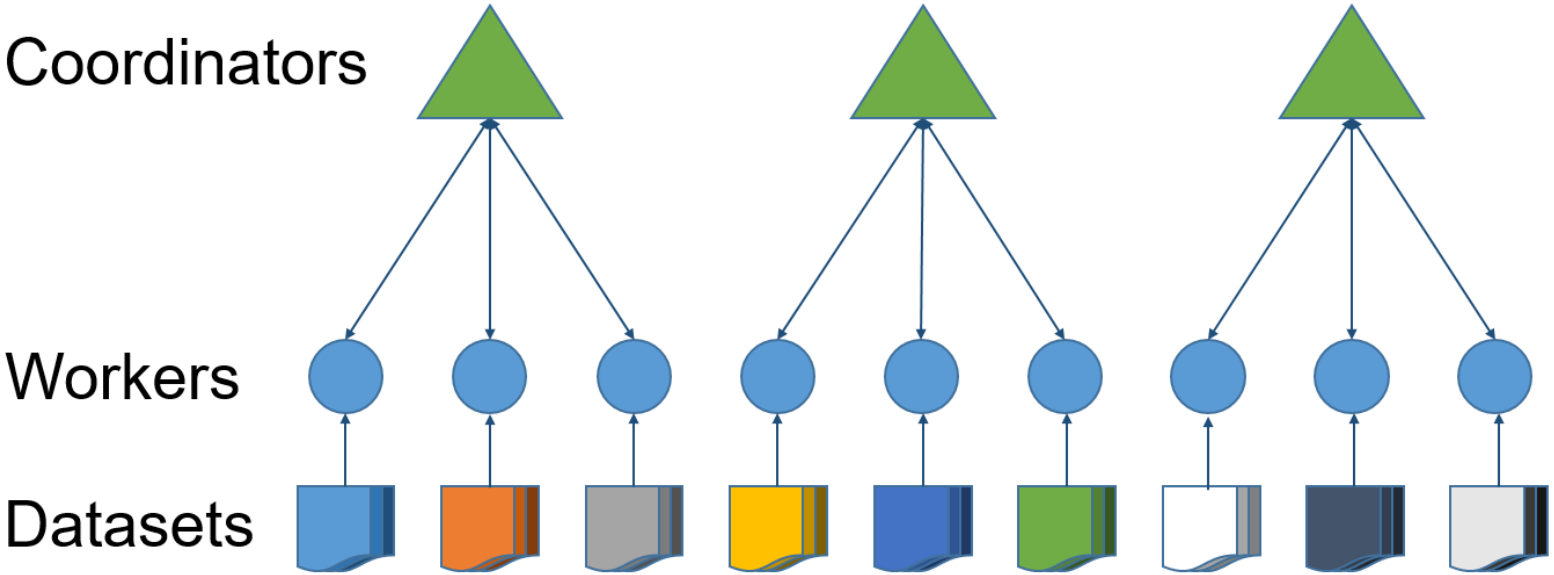
Ensemble of Local Models



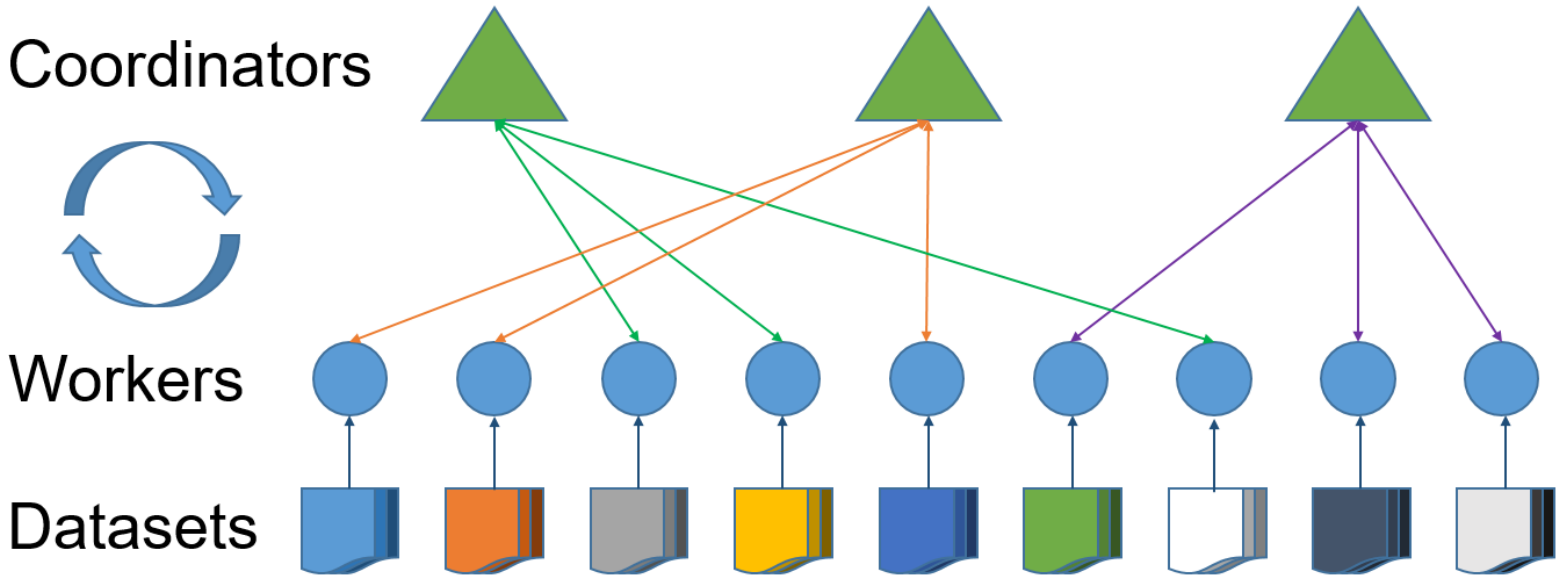
Ensemble of Global Models



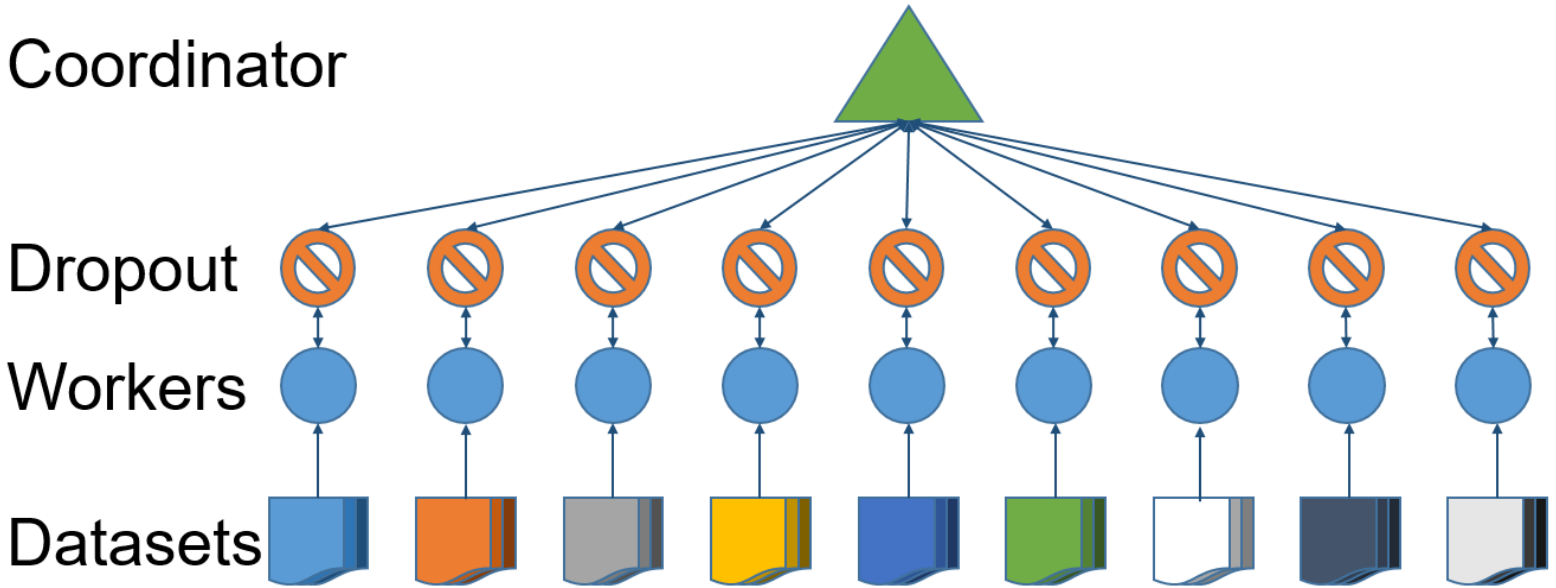
Ensemble w. mult. Coord. Fixed Assignement



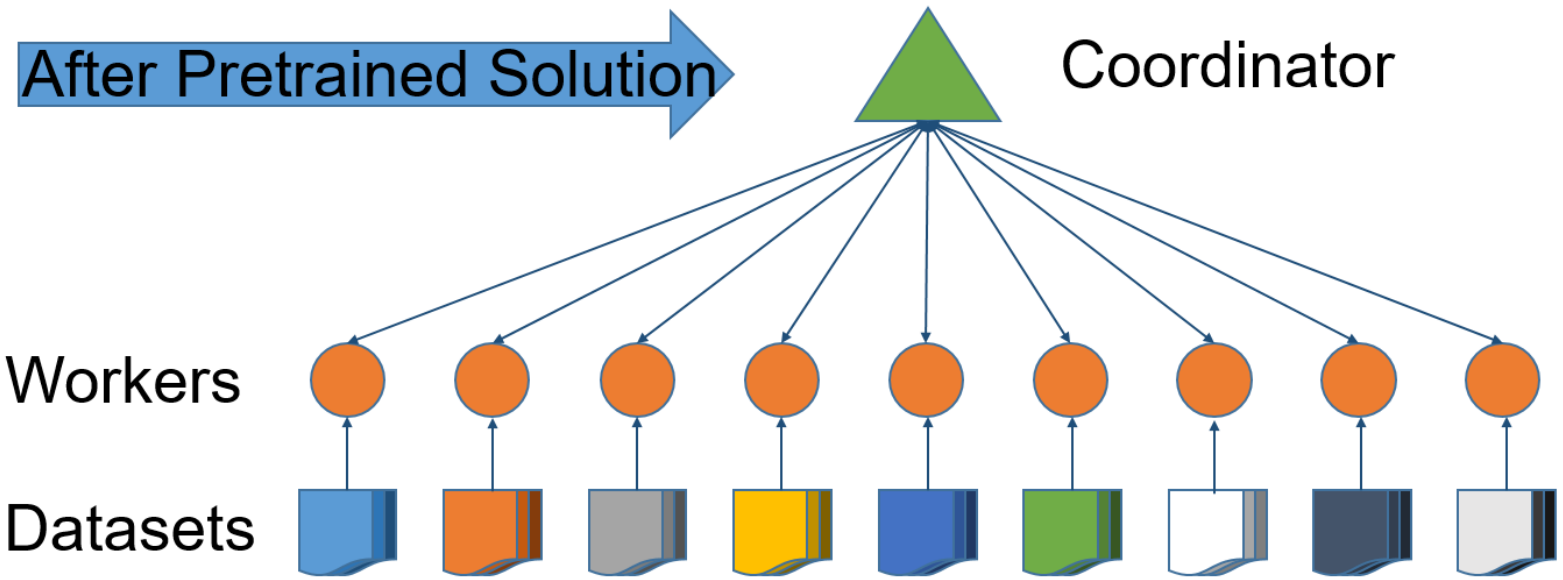
Ensemble w. mult. Coord. Random Assignement



Federated MC-Dropout



Federated SWAG



Chapter
Empirical Evaluation

Empirical Evaluation

Performance of Ensemble Approaches with CIFAR-10

		Detection of OOD (SVHN)		Detection of wrong classified Data	
	Accuracy	**Entropy AUROC**	**Variance AUROC**	**Entropy AUROC**	**Variance AUROC**
Global Model	86.58	0.924	-	0.888	-
Ensemble of local models	72.65	0.679	0.689	0.788	0.687
Ensemble of global models	**89.00**	**0.937**	**0.804**	**0.891**	**0.868**
Ensemble w. mult. Coord.-FA	83.43	0.860	0.740	0.858	0.815
Ensemble w. mult. Coord.-RA	86.72	0.920	0.750	0.887	0.861

Empirical Evaluation

Performance of MC-Dropout with CIFAR-10

		Detection of OOD (SVHN)		Detection of wrong classified Data	
	Accuracy	**Entropy AUROC**	**Variance AUROC**	**Entropy AUROC**	**Variance AUROC**
Global Model	77.88	0.742	-	0.838	-
Global Model with dropout	**86.58**	**0.924**	-	**0.888**	-
Federated MC-dropout	86.32	0.913	**0.714**	0.880	**0.849**

Empirical Evaluation

Performance of SWAG with CIFAR-10

		Detection of OOD (SVHN)		Detection of wrong classified Data	
	Accuracy	**Entropy AUROC**	**Variance AUROC**	**Entropy AUROC**	**Variance AUROC**
Global Model	86.58	0.924	-	0.888	-
Federated SWAG	**87.14**	**0.924**	**0.807**	**0.892**	**0.856**

Chapter
Conclusion

Conclusion

- Best Results in terms of accuracy and AUROC scores
  - Ensemble of Local Models
    - Best Accuracy
    - High Computational Overhead
  - Federated SWAG
    - Easy Integration in Running System
    - Doubled Communication during SWAG Training

Conclusion

- Multiple Coordinators
  - No Performance Increase
  - Might be suitable for moving devices like autonomous driving
- Dropout
  - Improves Performance when used as regularization
  - MC-Dropout does not improve performance

Chapter
Discussion

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