AI for IoT and Smart Cities

ISC2 Tutorial

Guillaume MULLER and
Kamal SINGH

{fname.lname}@univ-st-etienne.fr
Saint-Etienne, France

LABORATOIRE HUBERT CURIEN
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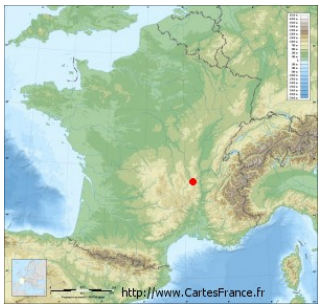

September 7, 2021

Outline

Outline

Inputs: Sensors

- Means to *collect* Data

From (Big) Data to Rich Services

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- Means to *collect* Data

Output: Actuators

- Means to *act* on the world

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Our Goal: Rich (Smart) Applications (IoT Examples)

Health Care plan operations, detect/predict diseases...

Smart Cities transport, energy saving...

From (Big) Data to Rich Services

Inputs: Sensors

- Means to *collect* Data
- Big Data
  - **V**olume, **V**elocity
  - **V**ariety, **V**eracity
  - **V**alue ...

Output: Actuators

- Means to *act* on the world

Our Goal: Rich (Smart) Applications (IoT Examples)

Health Care plan operations, detect/predict diseases...

Smart Cities transport, energy saving...

Smartness: Machine Learning (ML) / Data Science / AI

"Machine" $\Rightarrow$ Automatic

- 5 Vs
- Less human prior knowledge 

From (Big) Data to Rich Services

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"Learning" $\Rightarrow$ Adapt

- Distribution drift

From (Big) Data to Rich Services

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ML Goals

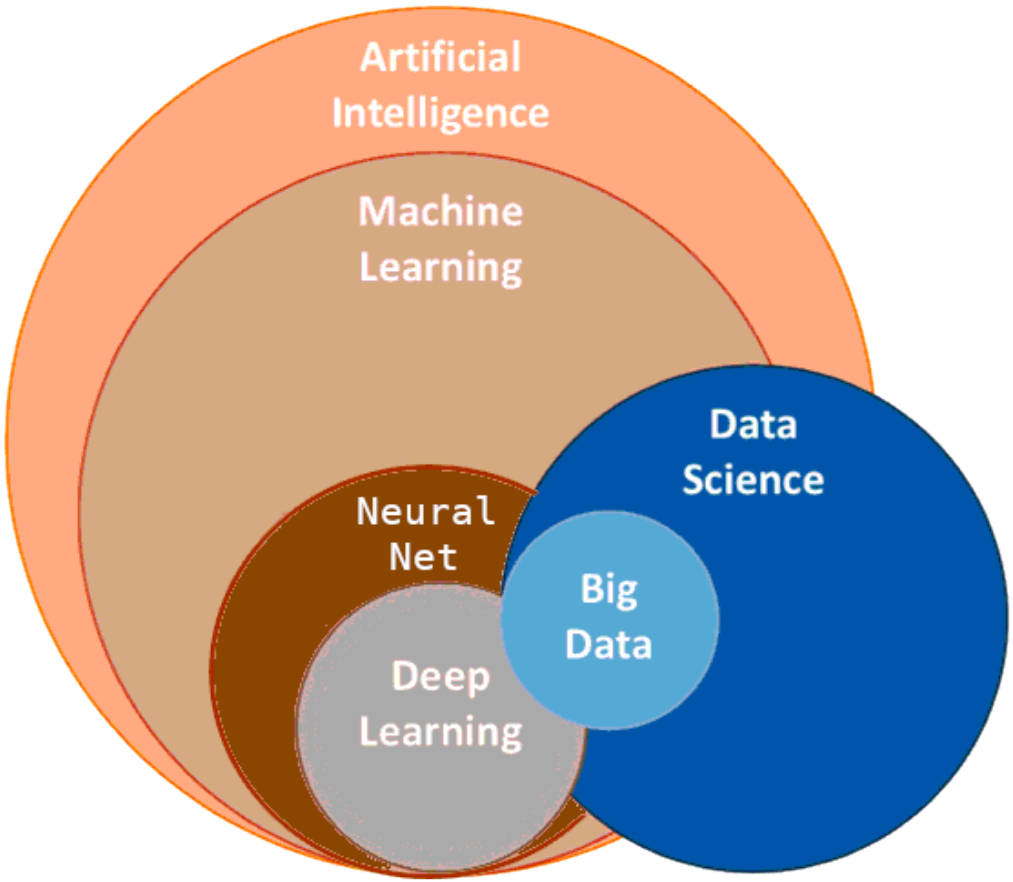
- Extract relevant information from raw data
  - Group/Rank elements, Predict values...
- Make relevant decisions based on this information
  - Take "optimal" decision

Big Data Market

"Data Scientist = Sexiest Job of 21st Century", HBR, 2012

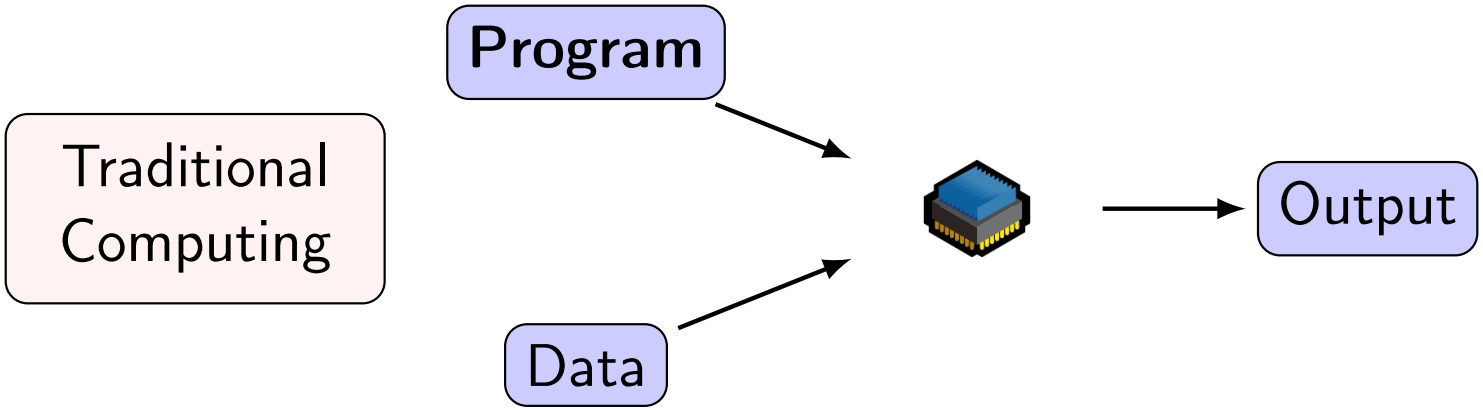
Outline

Big Data "Technologies"

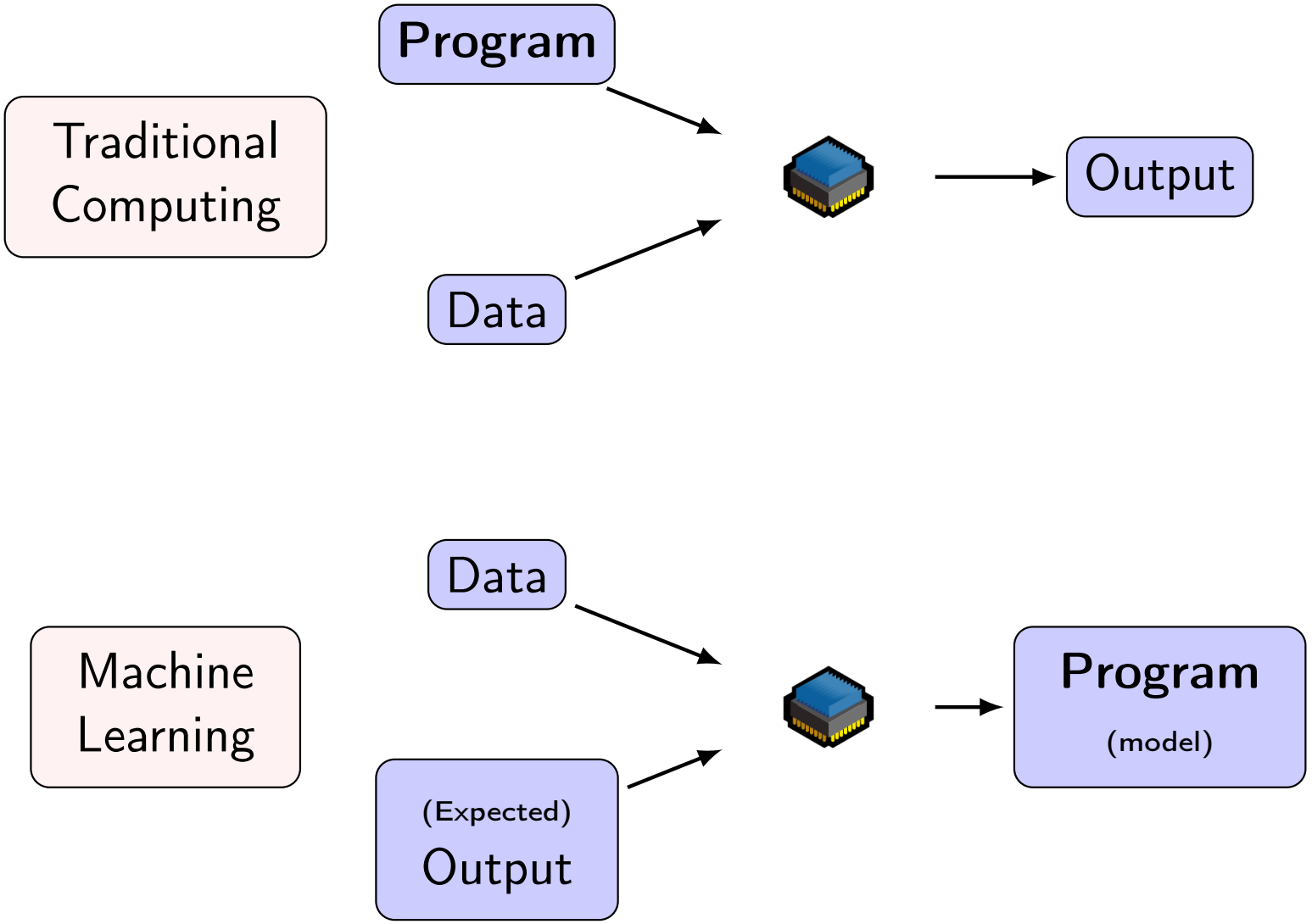


Based on: GMG Group

Machine Learning (vs. Traditional computing)

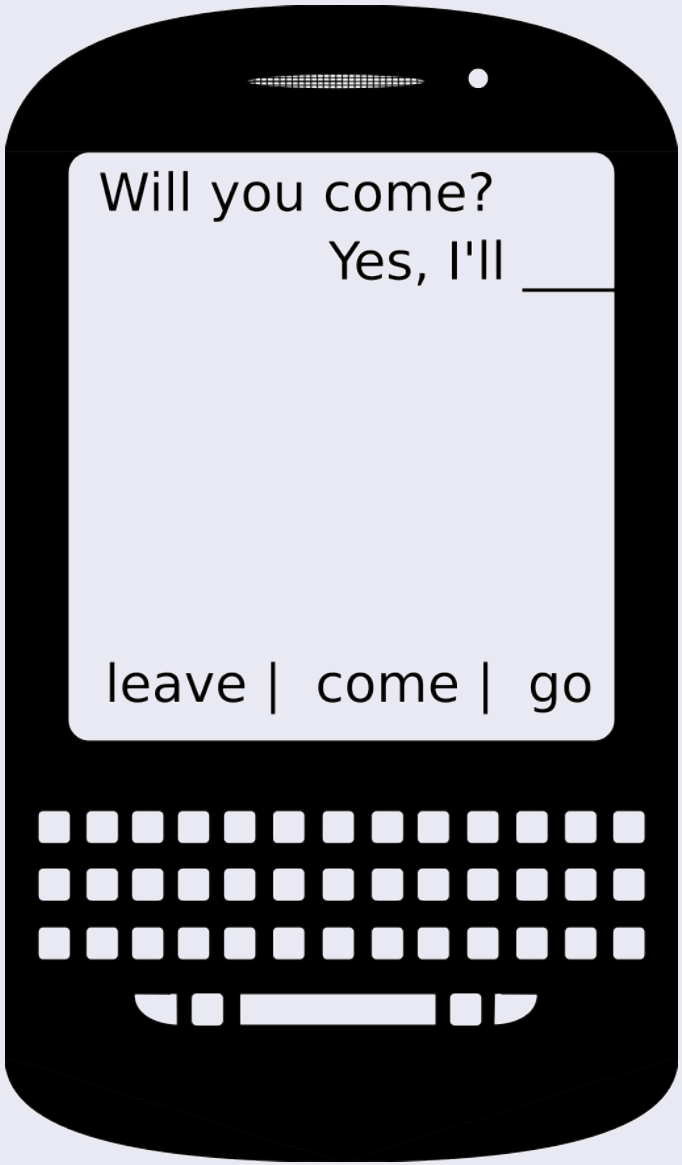


Machine Learning (vs. Traditional computing)



Machine Learning Example – Next Word Prediction

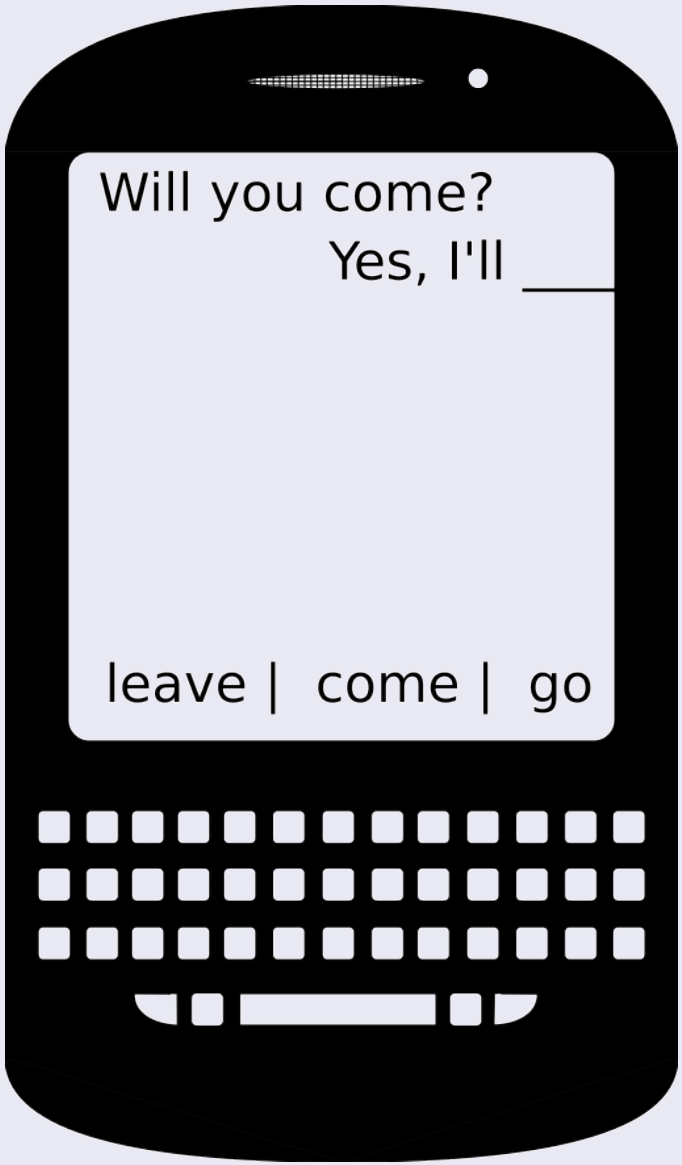
Machine Learning Example – Next Word Prediction



Machine Learning Process

- **Phase 1:** Train *@server*
  - Collect sentences
  - Compute "statistics"

Machine Learning Example – Next Word Prediction



Machine Learning Process

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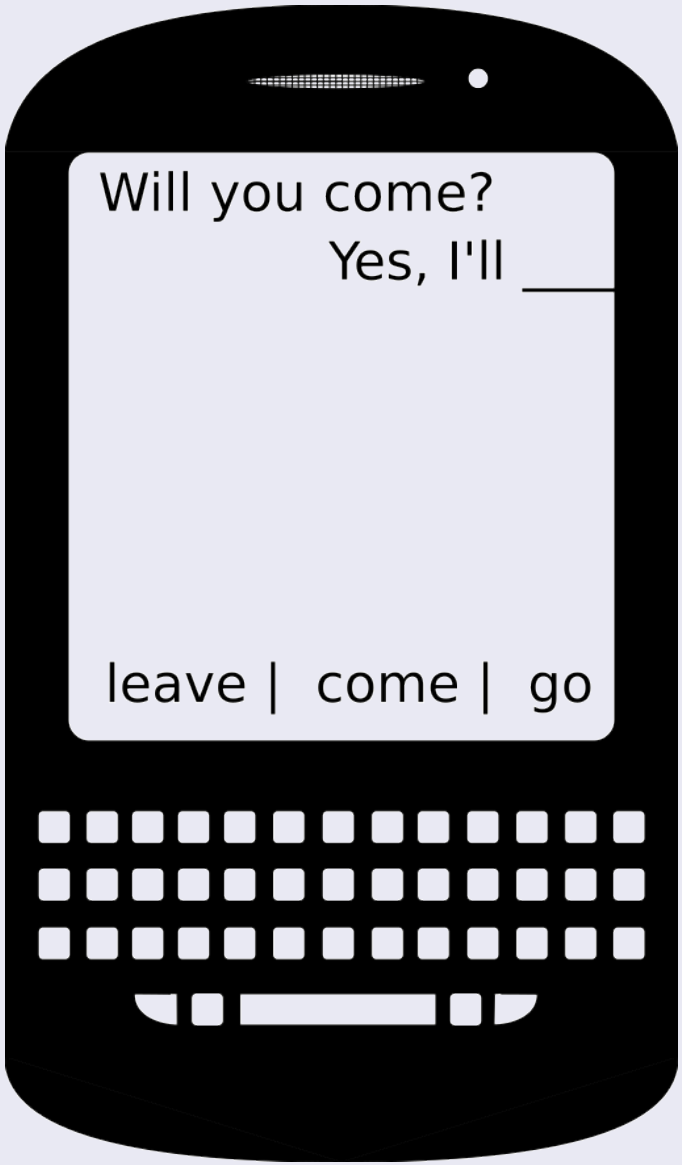
Trained Model

Machine Learning Example – Next Word Prediction



Machine Learning Process

- **Phase 1:** Train *@server*
  - Collect sentences
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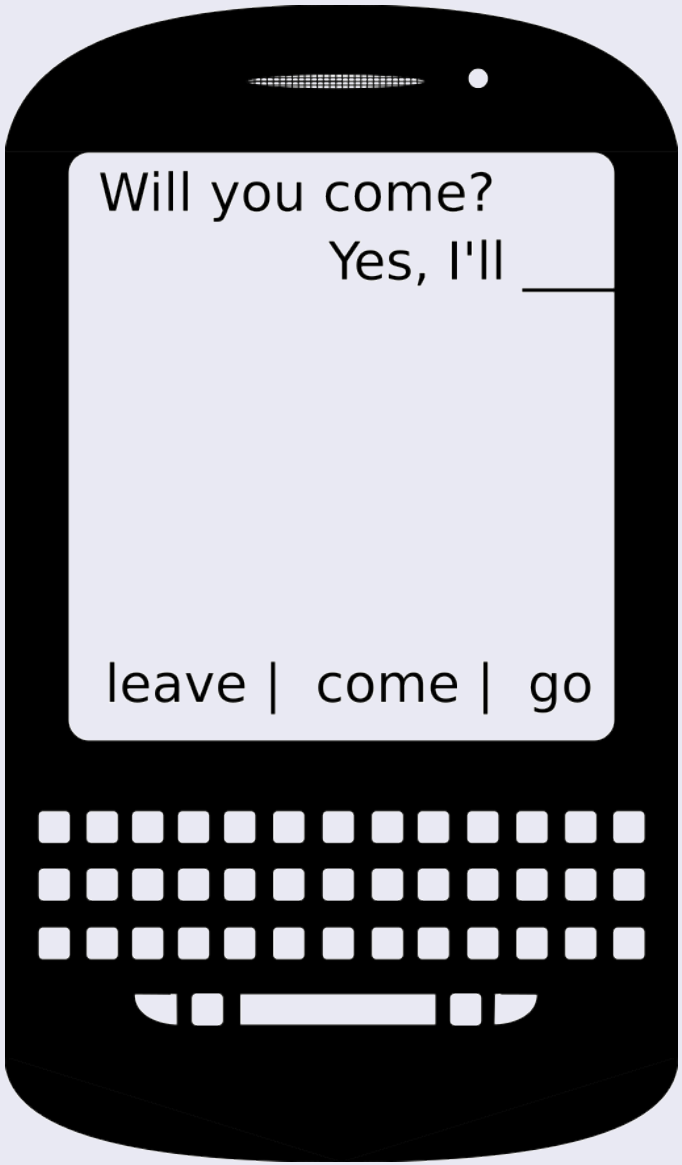
  - Evaluate performance (`loss`)

Trained Model

Machine Learning Example – Next Word Prediction



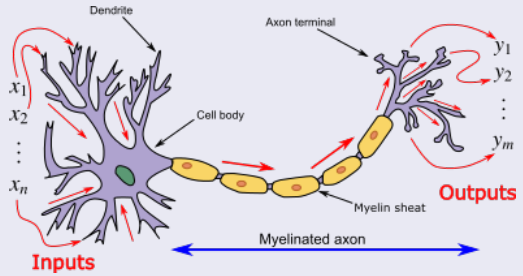
Machine Learning Process

- **Phase 1:** Train *@server*
  - Collect sentences
  - Compute "statistics"
  - Evaluate performance (`loss`)

Trained Model

- **Phase 2:** Use *@phone*
  - Get start of a sentence
  - Show most probable words

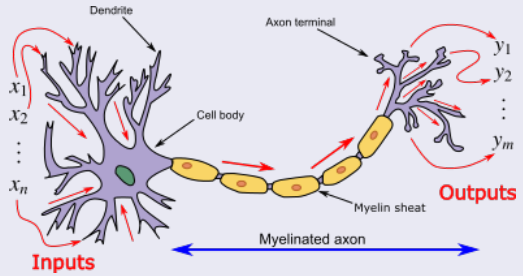
Biological Neuron



From: Prof. Loc Vu-Quoc

Neural Network (1 type of Machine Learning)

Biological Neuron



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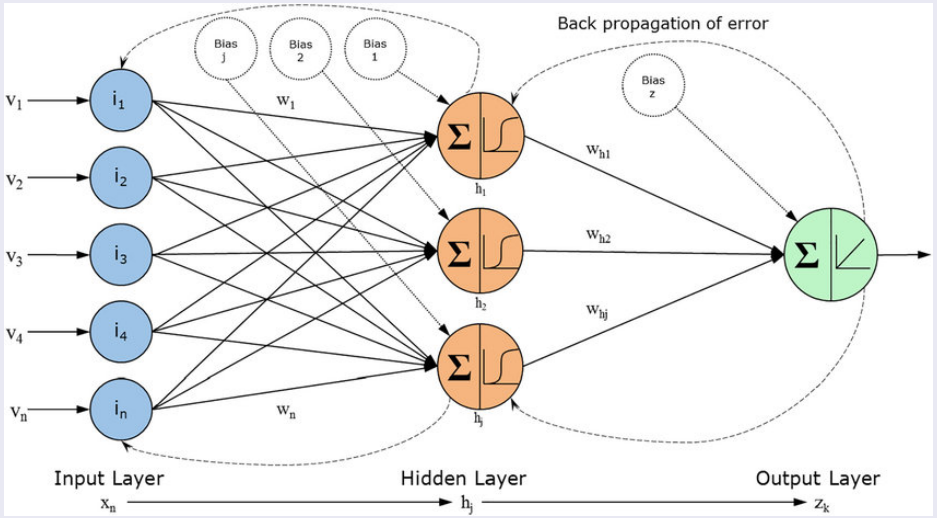
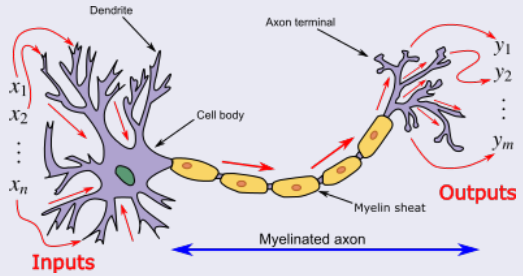
Artifical Neuron (Perceptron, Rosenblatt 1957)



From: D. Zafeiris, S. Rutella, G. R. Ball

Neural Network (1 type of Machine Learning)

Biological Neuron



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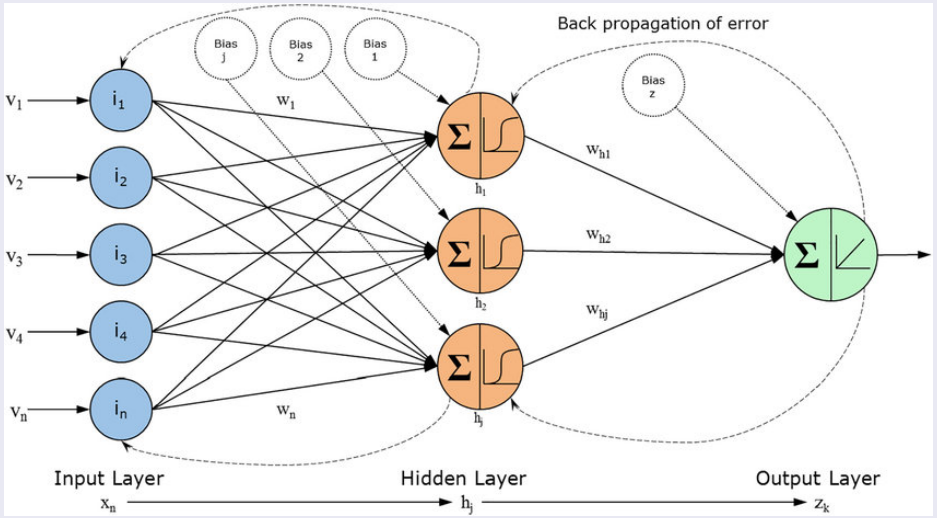
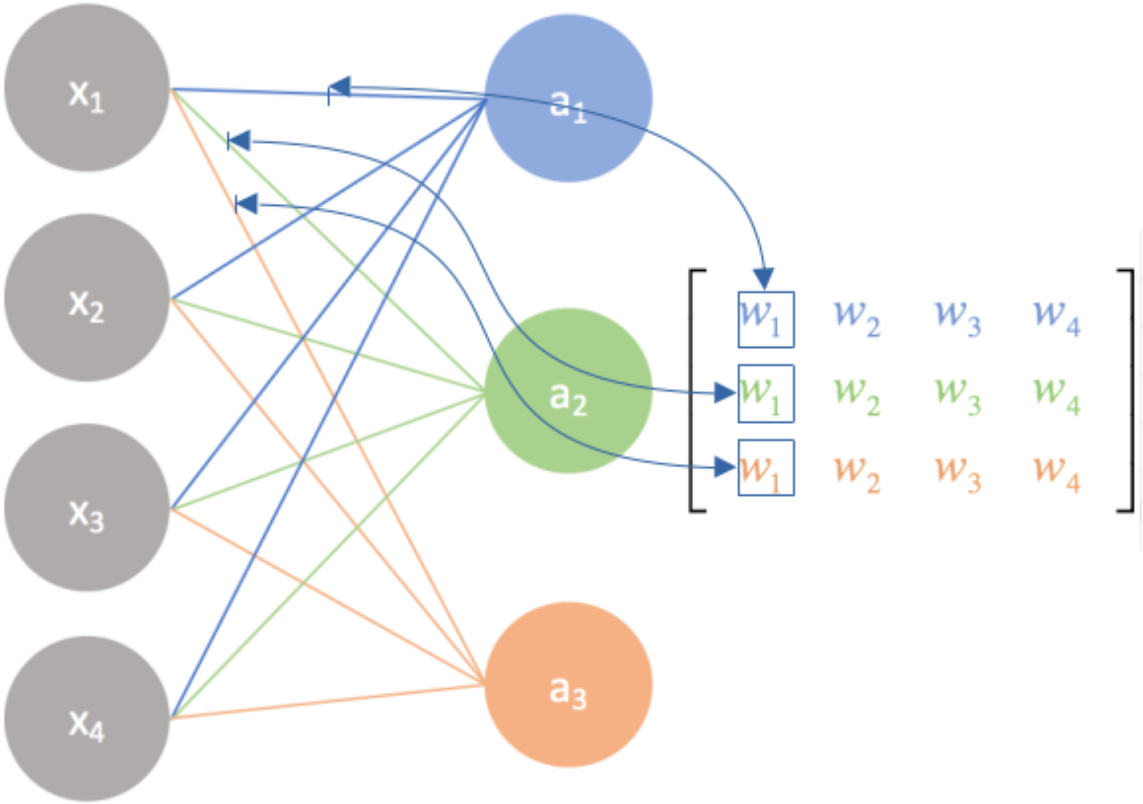


From: D. Zafeiris, S. Rutella, G. R. Ball

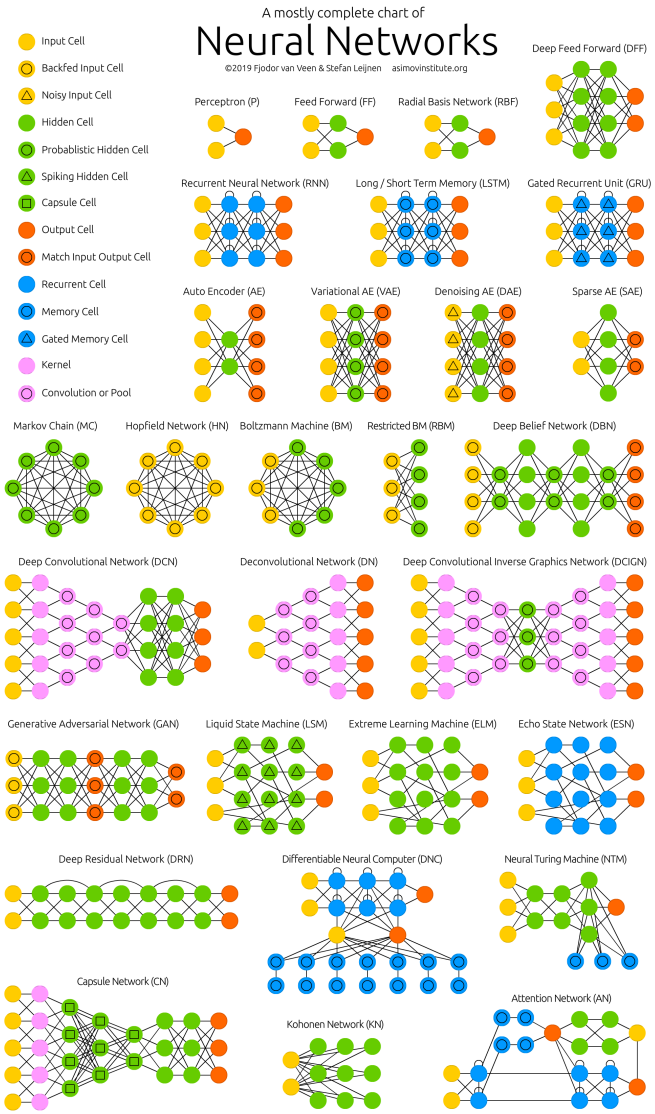
All numbers!

(Artificial) Neural Network as Matrices



From: jeremyjordan.me

(Artificial) Neural Network Zoo



From: Asimov Institute

Section Outline

Basics

- Feed Forward NN
- Recurrent NN
- Convolutional NN
- Auto-Encoder

State-of-the-art

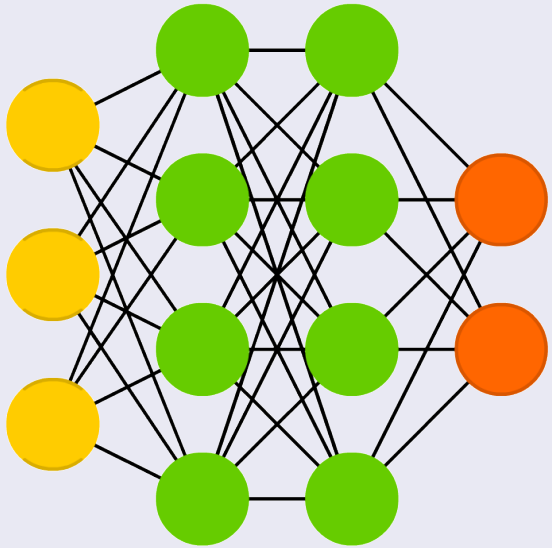
- Variational Auto-Encoder
- Generative Adversarial Network
- Attention Network

One/Few-shot training

- Siamese Networks

Feed Forward NN (MLP/FCN, Rosenblatt 1961)

Deep Feed Forward (DFF)



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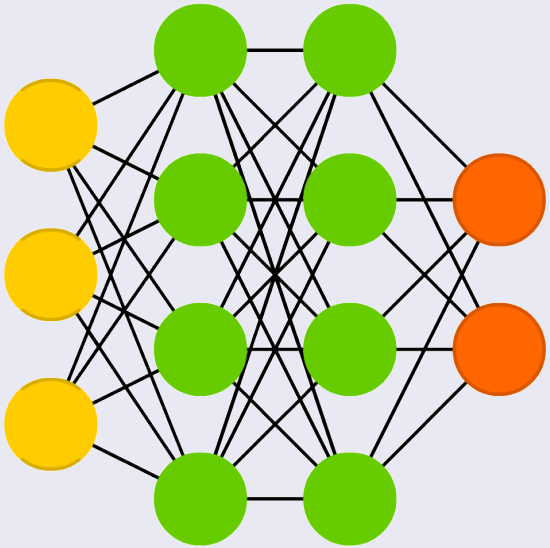
Feed Forward NN (MLP/FCN, Rosenblatt 1961)

Deep Feed Forward (DFF)

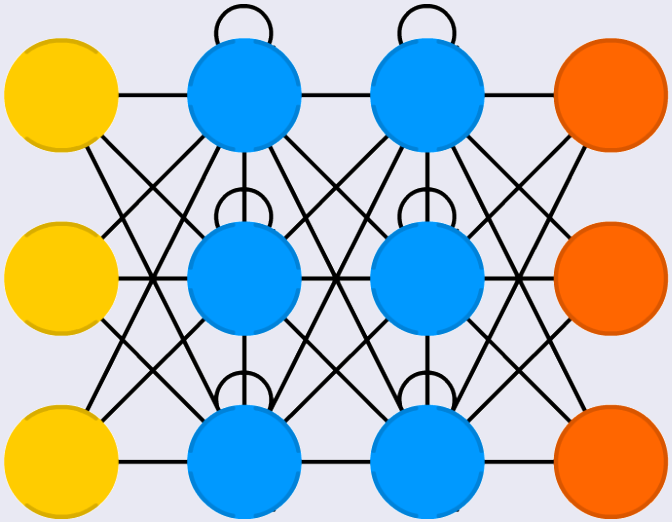


From: Asimov Institute

- Feed: Forward
- Train: Backward
  - Backpropagation
  - Gradient Descent

Recurrent Neural Network (RNN, Rumelhart 1986)

Recurrent Neural Network



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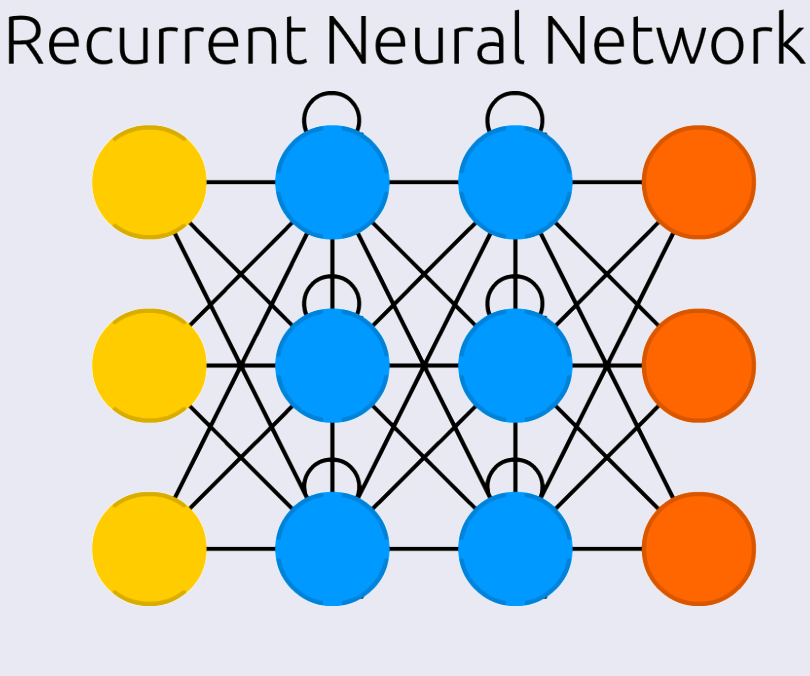
Recurrent Neural Network (RNN, Rumelhart 1986)

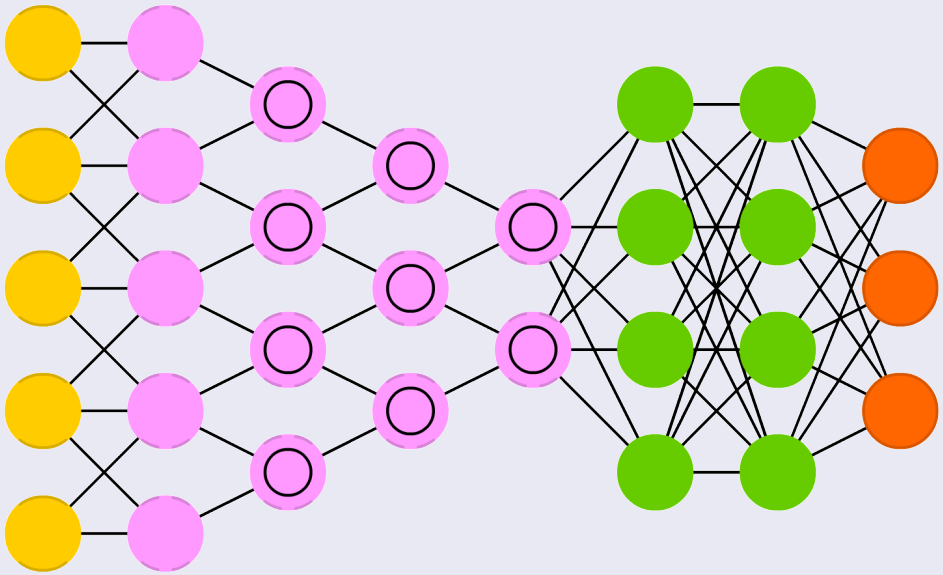


From: Asimov Institute

- For Sequences, Time Series (Memory)
- Harder to train: Vanishing/Exploding Gradient
- Improvements: LSTM / GRU

Convolutional Neural Network (CNN, Lecun 1989)

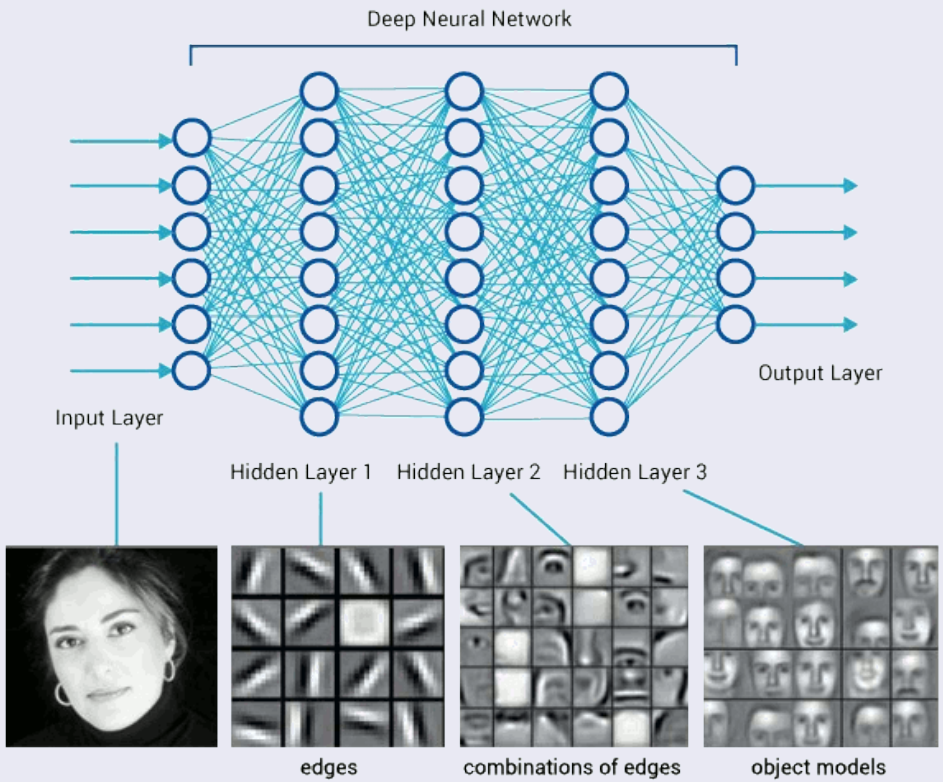
Deep Convolutional Network (DCN)



From: Asimov Institute

- Convolutions = filters (e.g. edge detector)

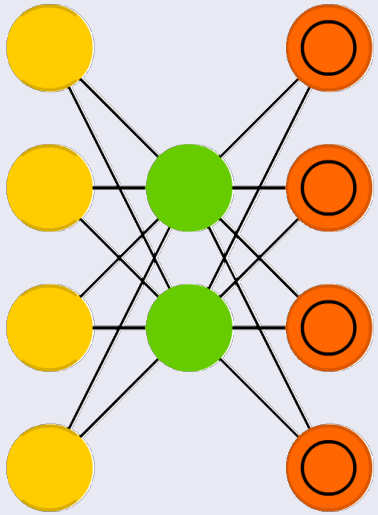
Convolutional Neural Network (CNN, Lecun 1989)



From: diary of a wannapreneur

Auto-Encoder (AE, Lecun 1987, Kramer 1991, Hinton 1994)

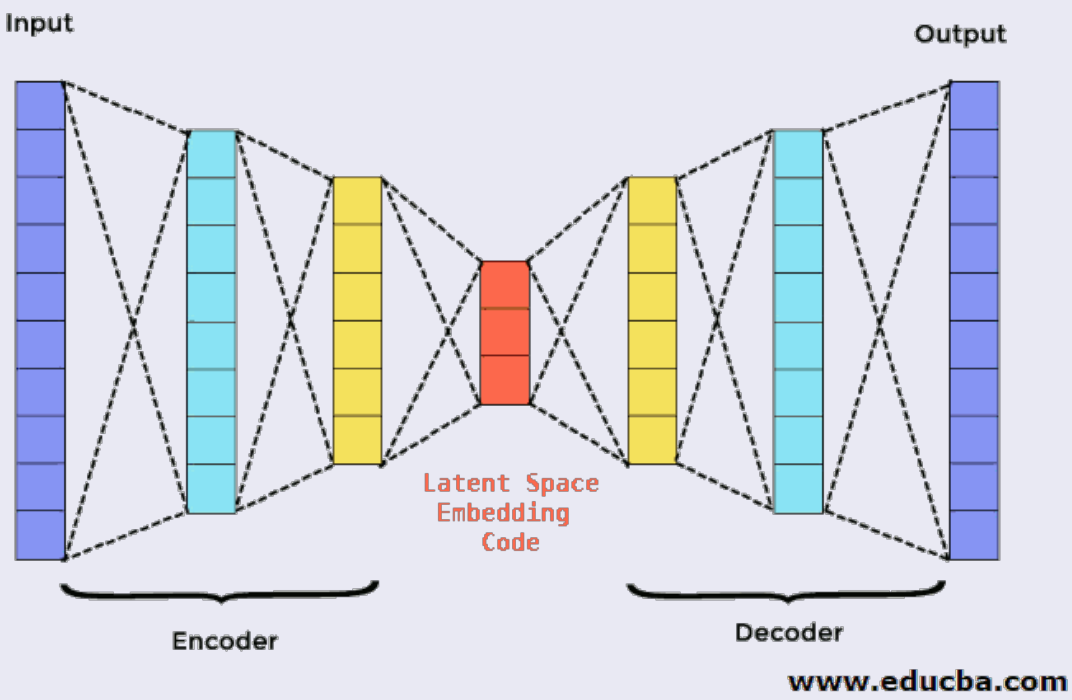
Auto Encoder (AE)



From: Asimov Institute

- Symmetrical
- Feature Engineering / Unsupervised

Auto-Encoder (AE, Lecun 1987, Kramer 1991, Hinton 1994)



From: EducBA

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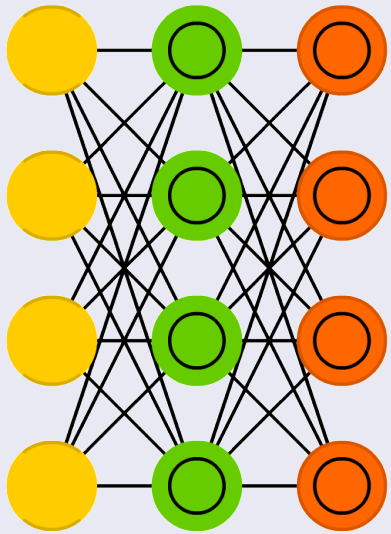
- Siamese Networks

Variational Auto-Encoder (VAE, Kingma 2014)

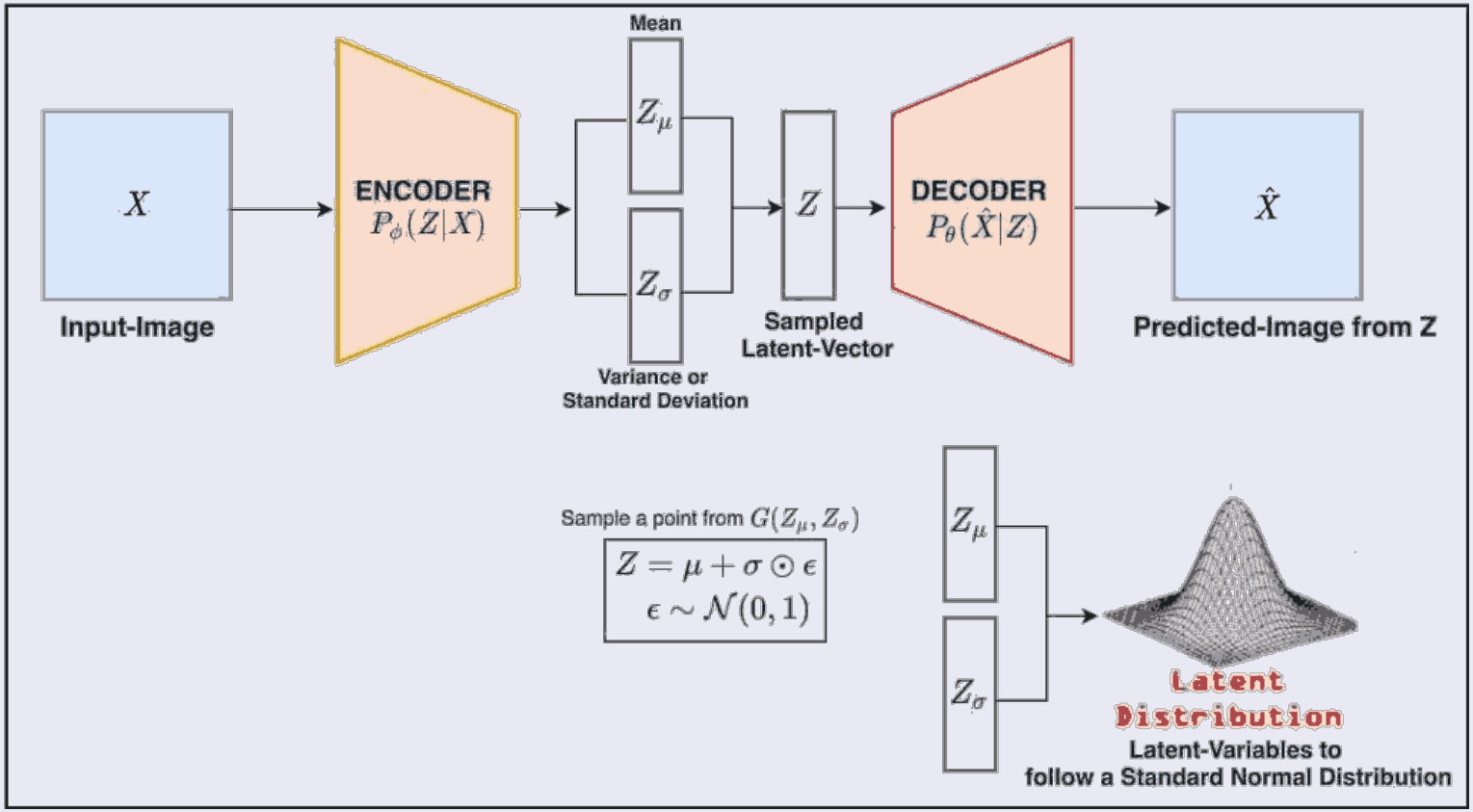
Variational AE (VAE)



From: Asimov Institute

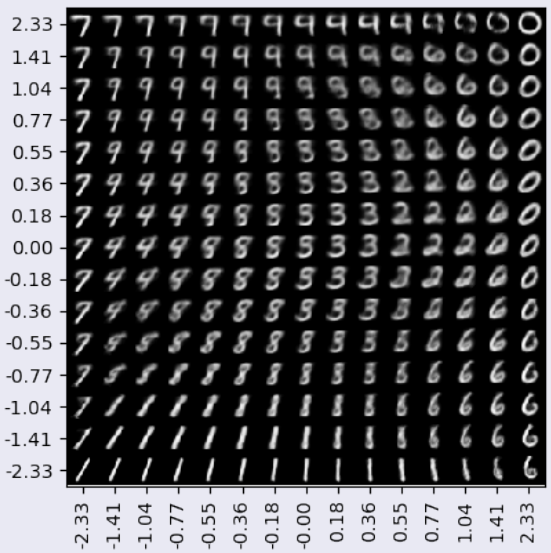
- Latent Space = Normal Distribution
- Can be used to generate data

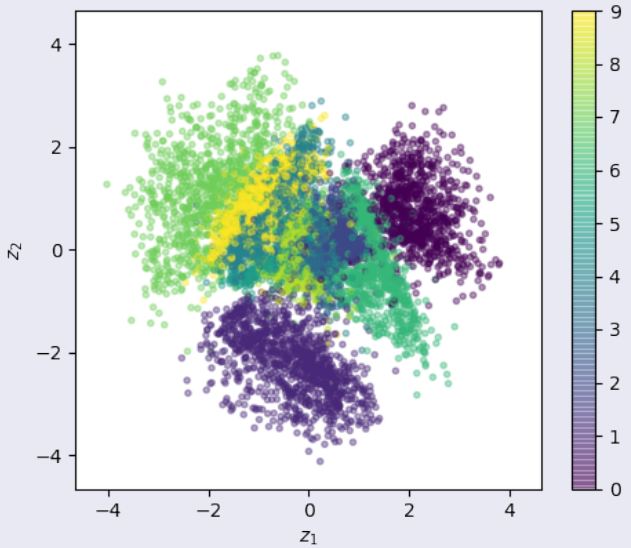
Variational Auto-Encoder (VAE, Kingma 2014)



From: Learn OpenCV

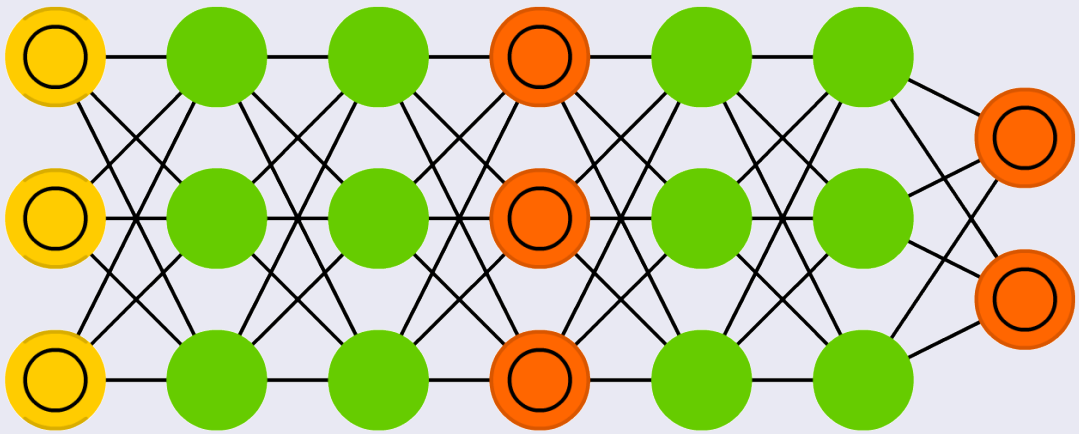
Variational Auto-Encoder (VAE, Kingma 2014)





From: tioao.io

Generative Adversarial Network (GAN)



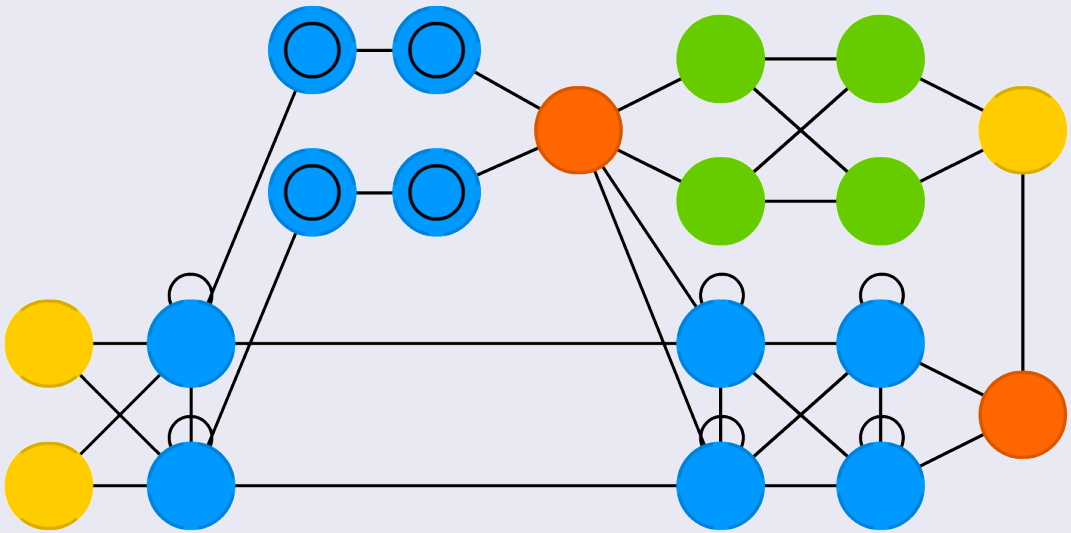
From: Asimov Institute

Generative Adversarial Network (GAN, Goodfellow 2014)

From: Towards Datascience

- "Old" AI Principle of Co-evolution
- Can be used to generate data

Attention Network (Vaswani 2017)



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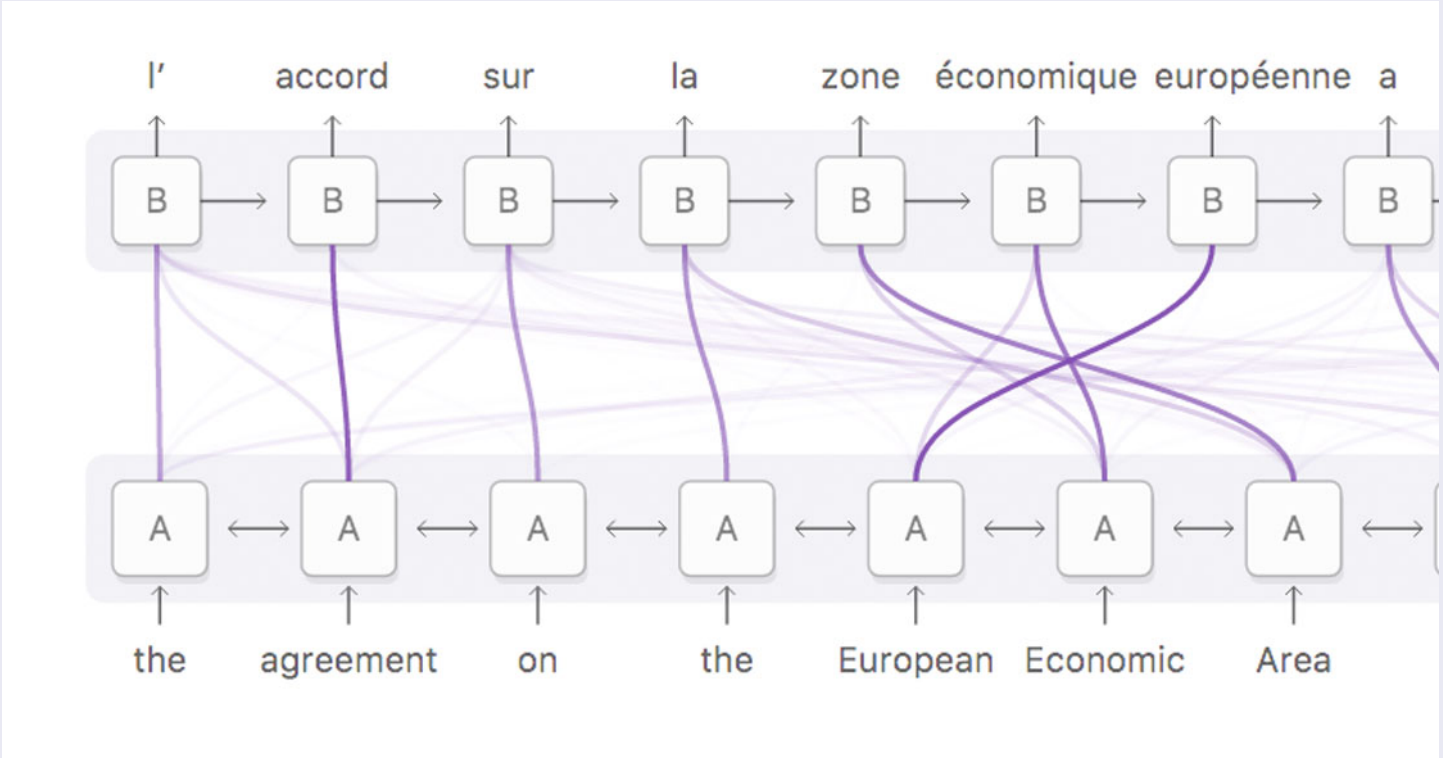


From: C. Olah, S. Carter (Google Brain) @Distill

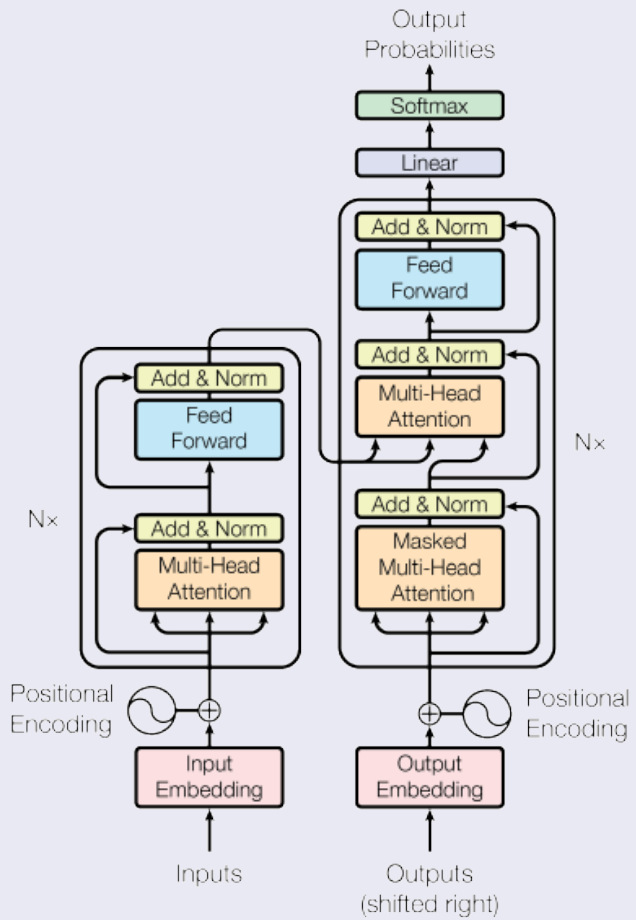
Attention Network (Vaswani 2017)

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

From: "Show, attend and tell...", K. Xu *et al* 2015.

Attention Network (Vaswani 2017)



- From: "Attention is all you need", A. Vaswani *et al*, 2017.

- Transformers
  - BERT, GPT-3...
- "Replaces" RNN, CNN

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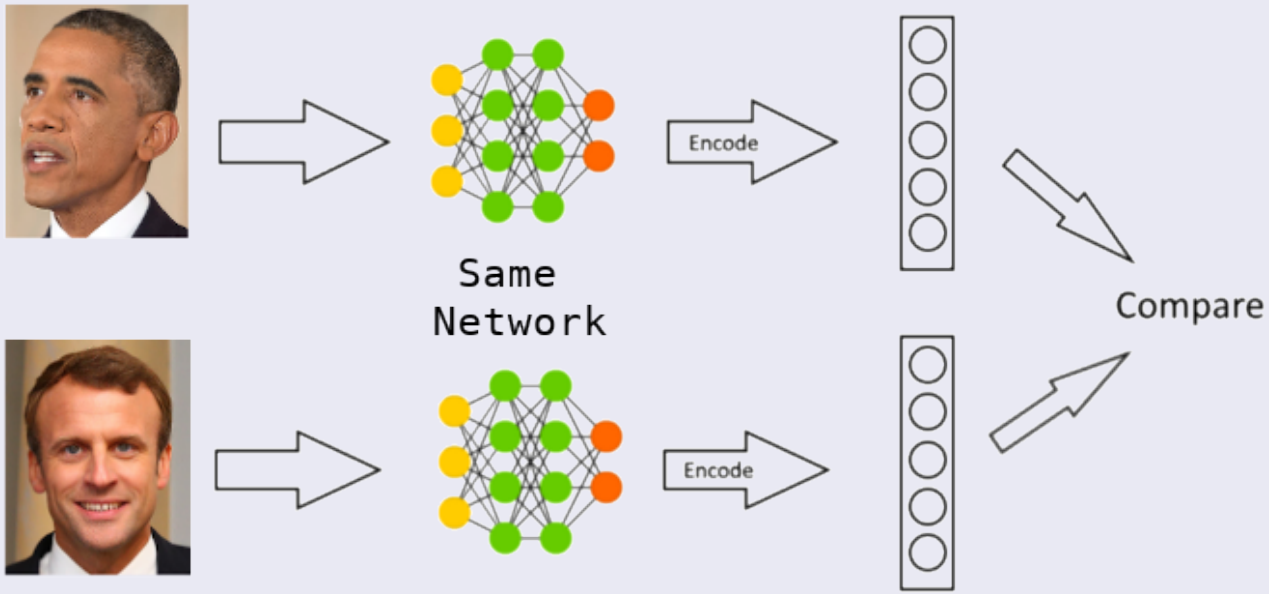
- Siamese Networks

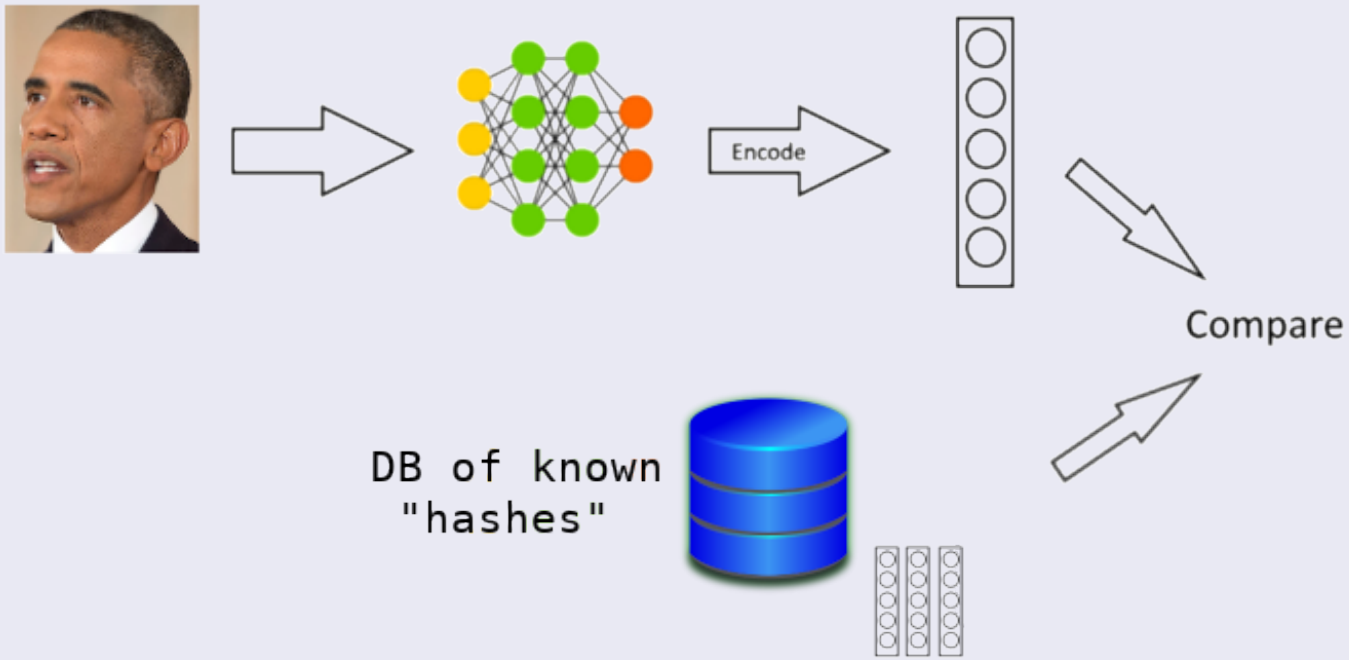
One/Few-Shot Learning (Bromley 1994, Chopra 2005)



Based on: E. Craeymeersch

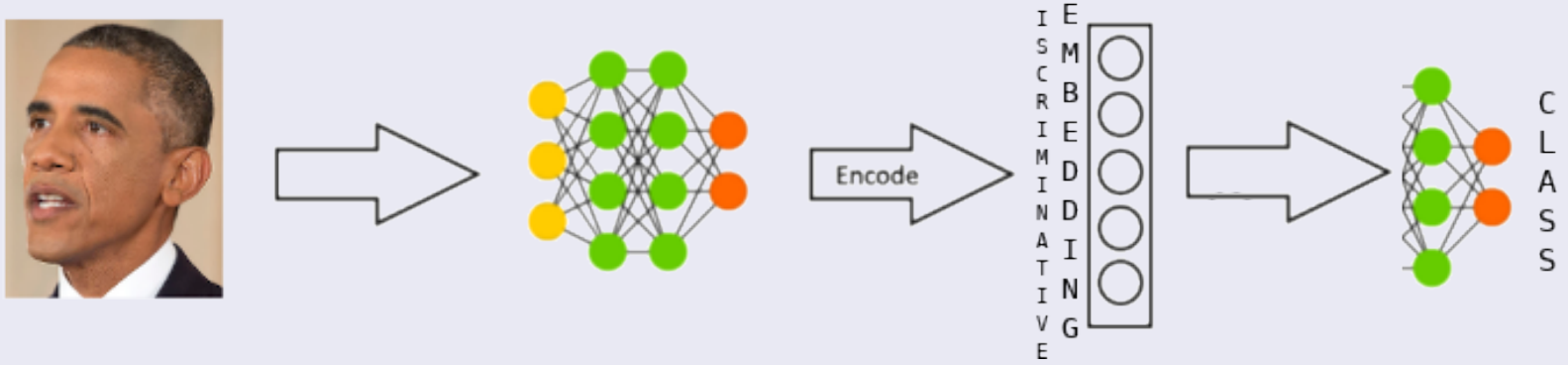
- "Siamese" Network
- When few data is available

One/Few-Shot Learning (Bromley 1994, Chopra 2005)



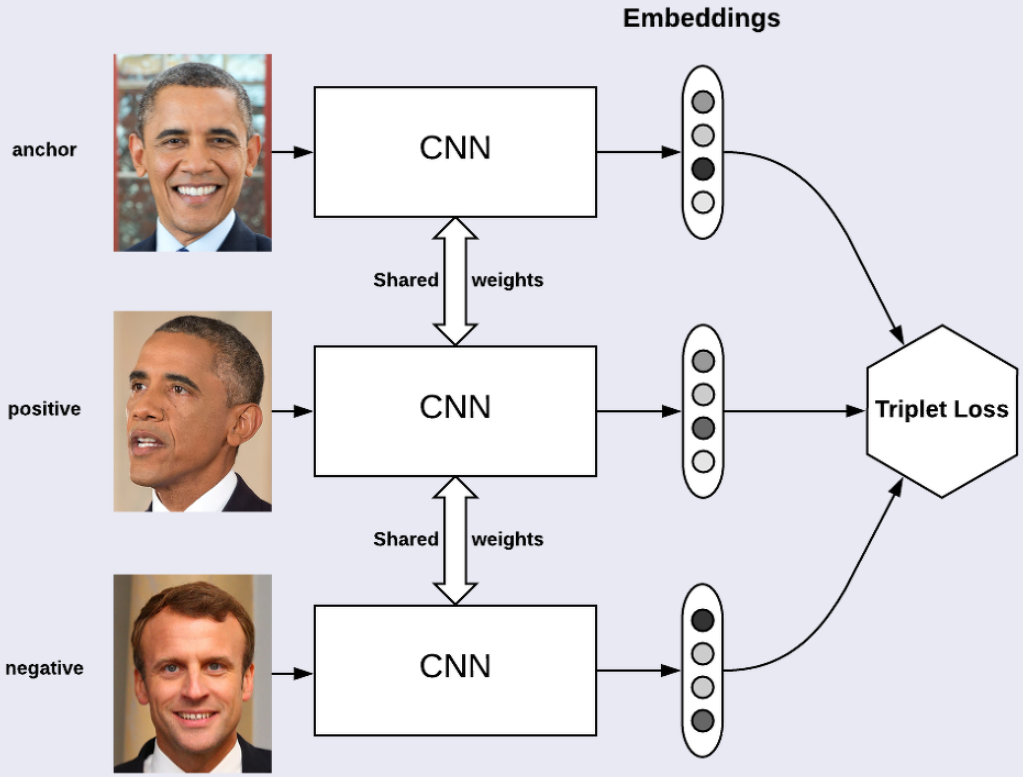
- Example: Mobile Phone facial recognition
- Same principle as Hashed passwords

One/Few-Shot Learning (Bromley 1994, Chopra 2005)



- For classification
- Concatenate a FCN at the end
- Siamese vs. FCN: discriminative latent space / few data

One/Few-Shot Learning (Bromley 1994, Chopra 2005)



From: Deep Play

- Finds most discriminative latent space (distance)
- Requires less input data (pairs, triplets)

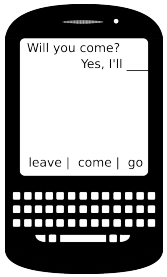
How to train these models?

Deep Neural Networks

- Billions of parameters to tune
- $\Rightarrow$ Billions of data!

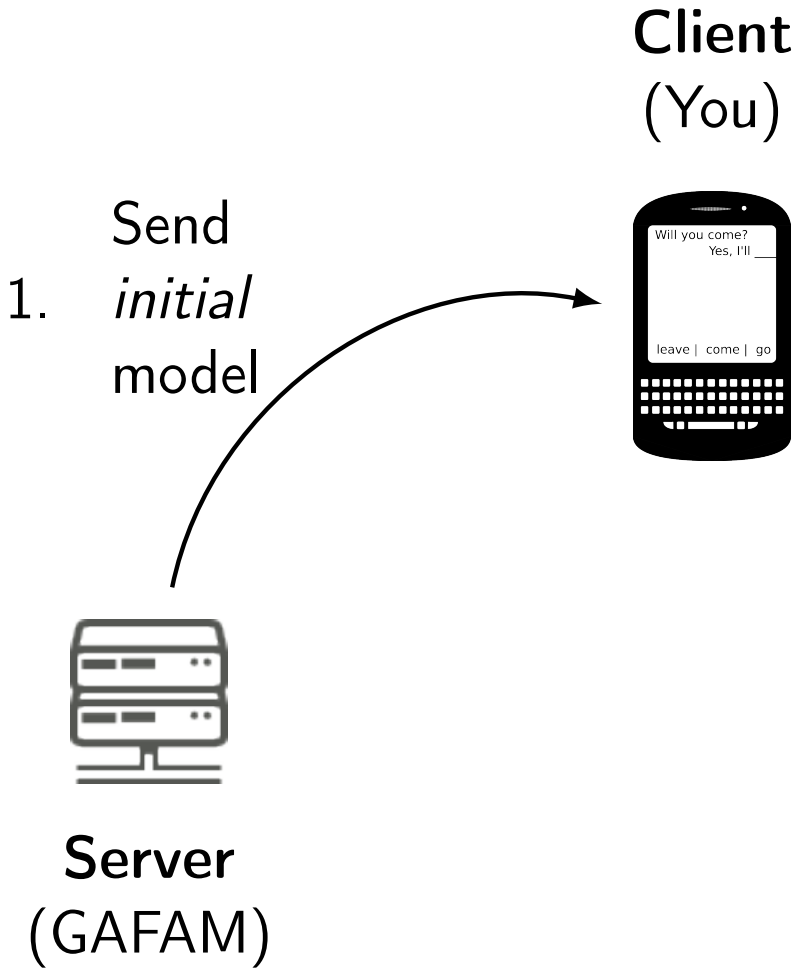
"Traditional" Machine Learning

Client
(You)



Server
(GAFAM)

"Traditional" Machine Learning



"Traditional" Machine Learning

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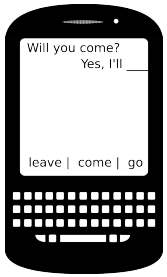
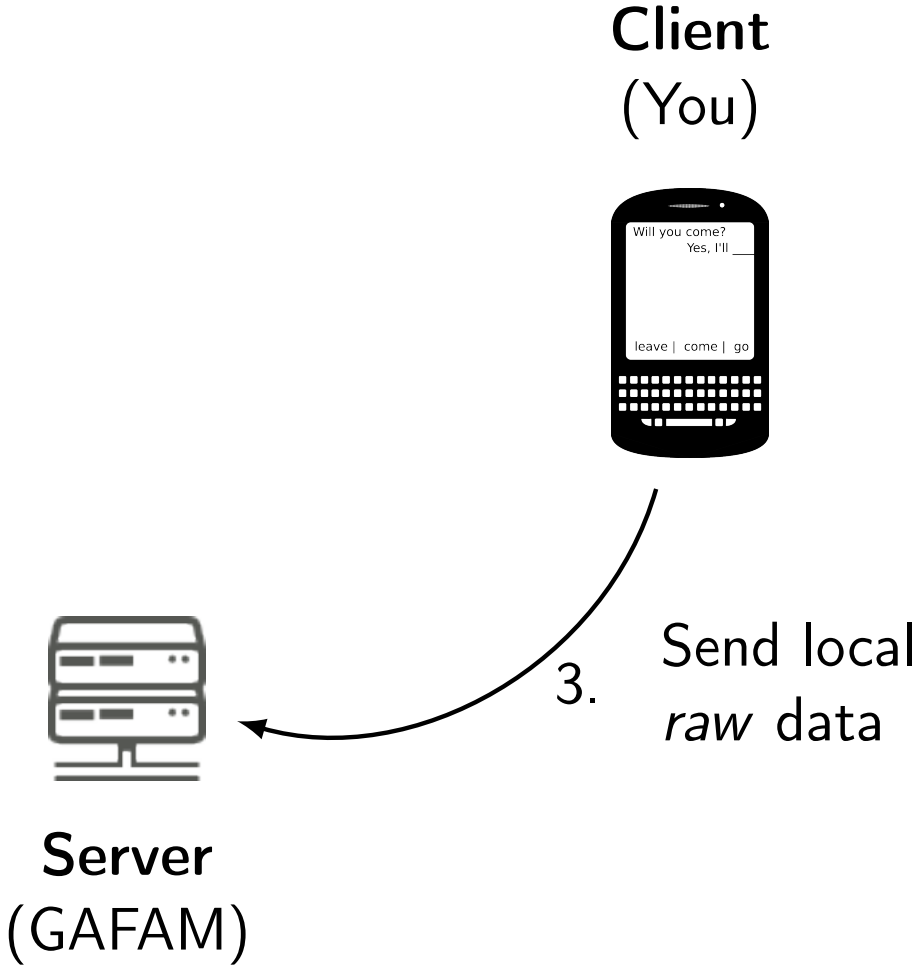


2.

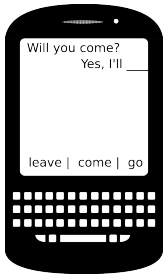
- *Use* model
- Collect data

Server
(GAFAM)

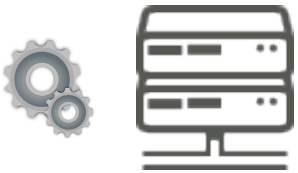
"Traditional" Machine Learning



Client
(You)

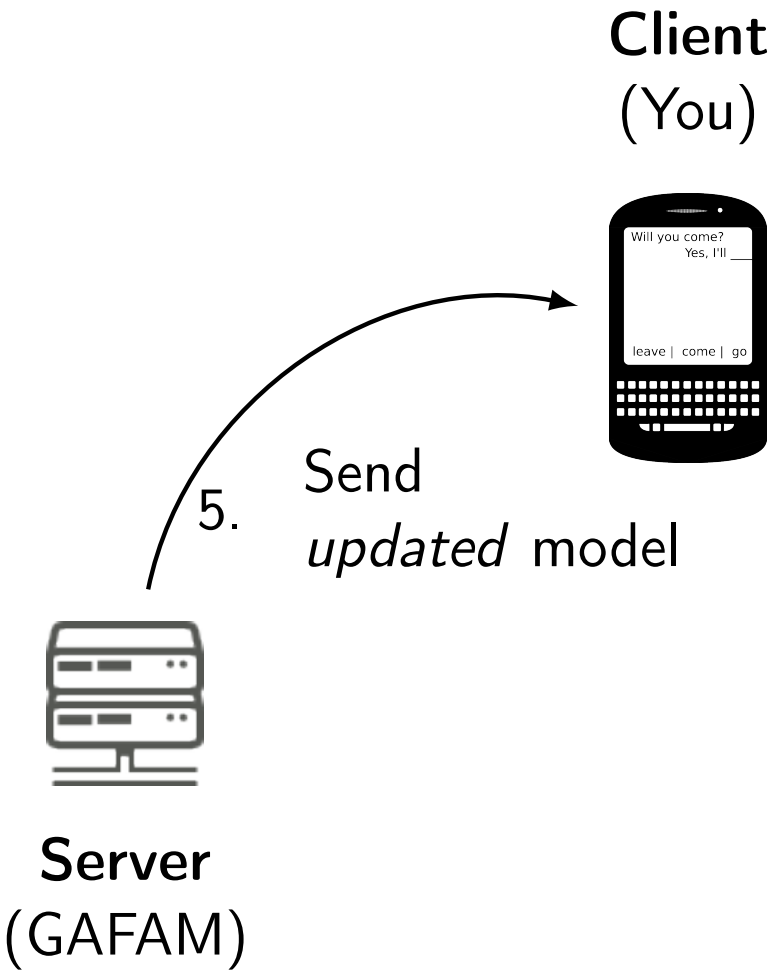


4. (re)Train model

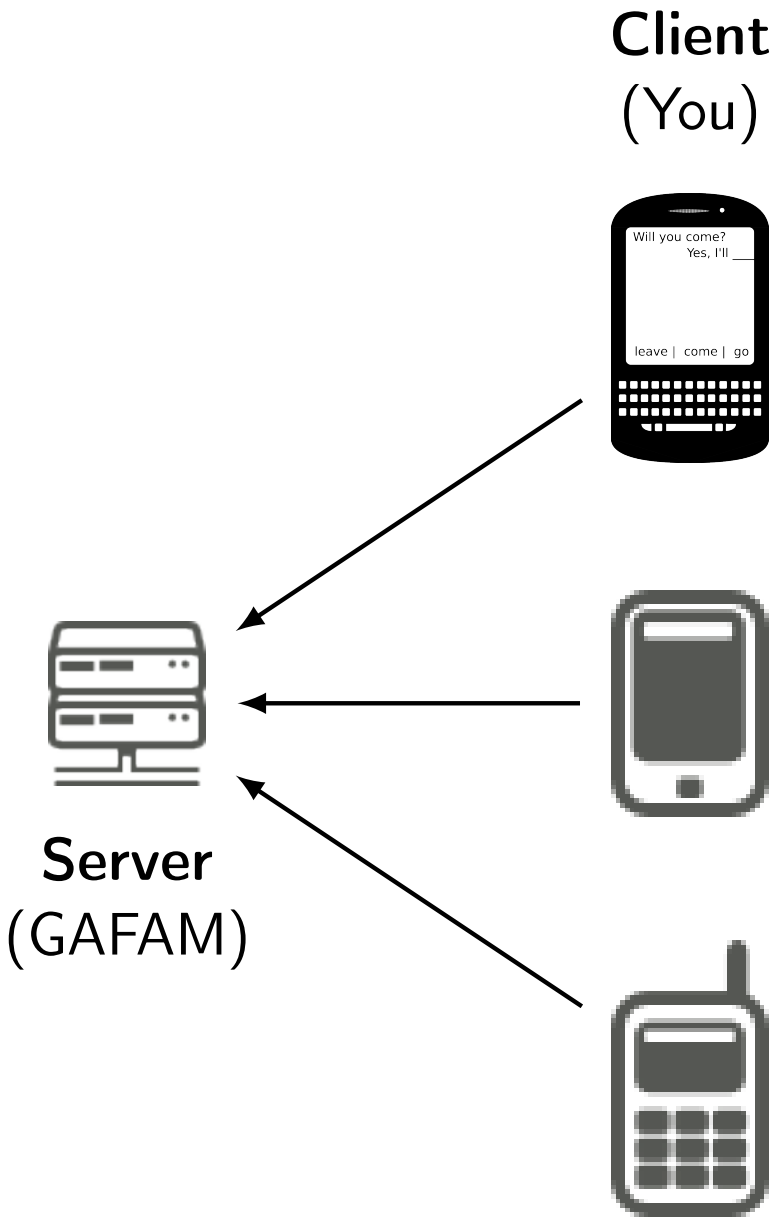


Server
(GAFAM)

"Traditional" Machine Learning



"Traditional" Machine Learning



Problem!

- Single device
  - sensitive data
- Multiple devices
  - crossed data

"Traditional" Machine Learning – Limits

Privacy Problem...

- Keyboard = everything
  - Passwords
  - Sensitive messages
  - Visited websites
  - ...

Efficiency Problem...

- Raw data = ⚖
  - Images
  - Videos
  - Sound
  - ...

"Traditional" Machine Learning – Limits

Privacy Problem...

- Keyboard = everything
  - Passwords
  - Sensitive messages
  - Visited websites
  - ...

...in general

- "Data is the new Oil"
- Health Care (ECG, EEG), Industry 4.0 (Machine logs)...
  - $\Rightarrow$ Diseases, IP...

Efficiency Problem...

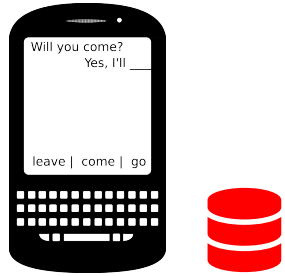
- Raw data = ⚖
  - Images
  - Videos
  - Sound
  - ...

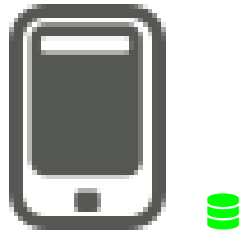
...in general

- Network Traffic
- Server Load

Outline

Federated Learning – Principle

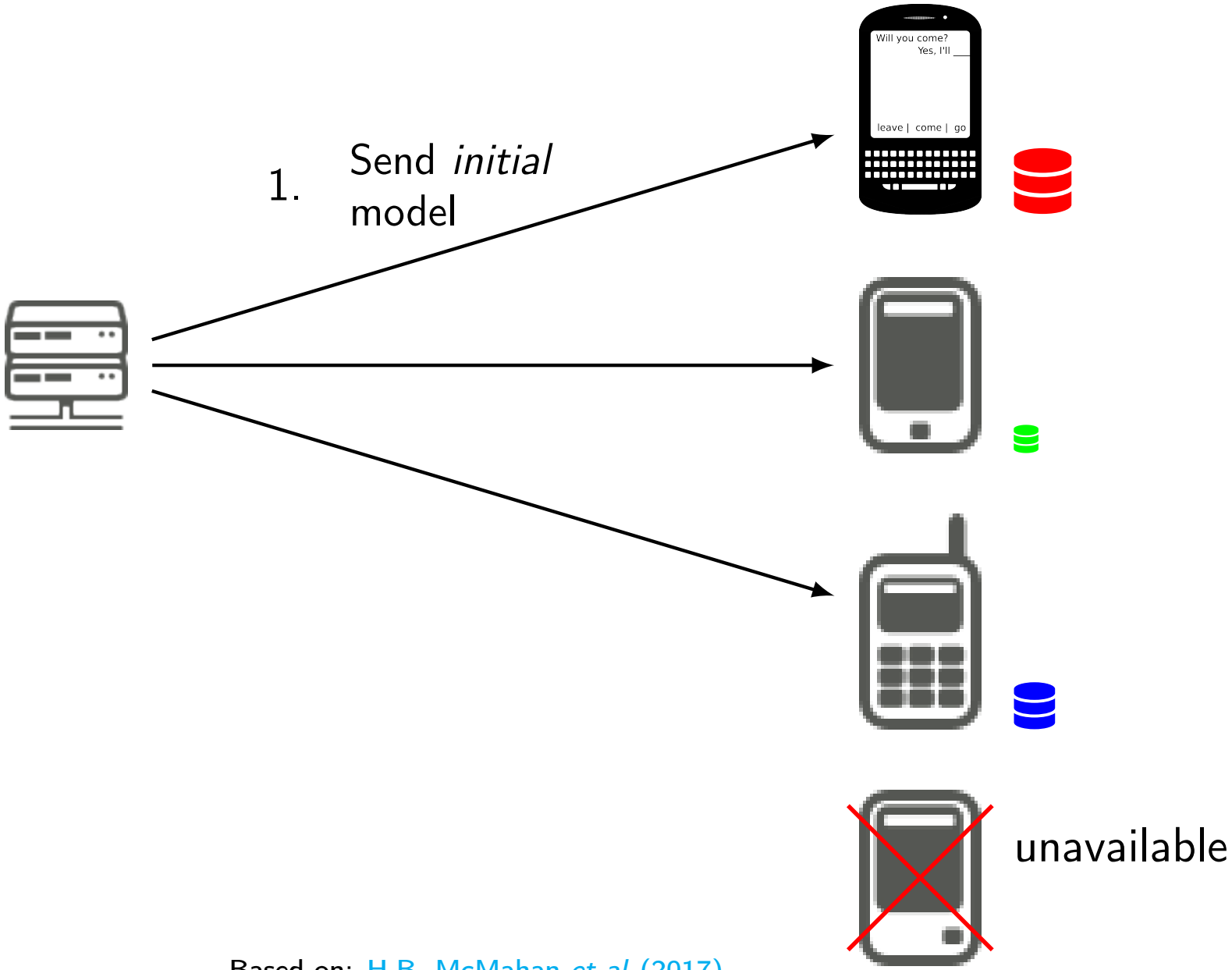




unavailable

Based on: H.B. McMahan *et al* (2017)

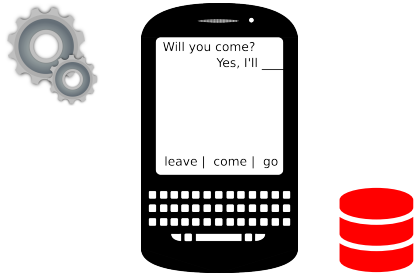
Federated Learning – Principle

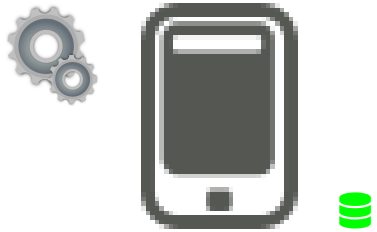


Based on: H.B. McMahan *et al* (2017)

Federated Learning – Principle

2. Train model on *local* data





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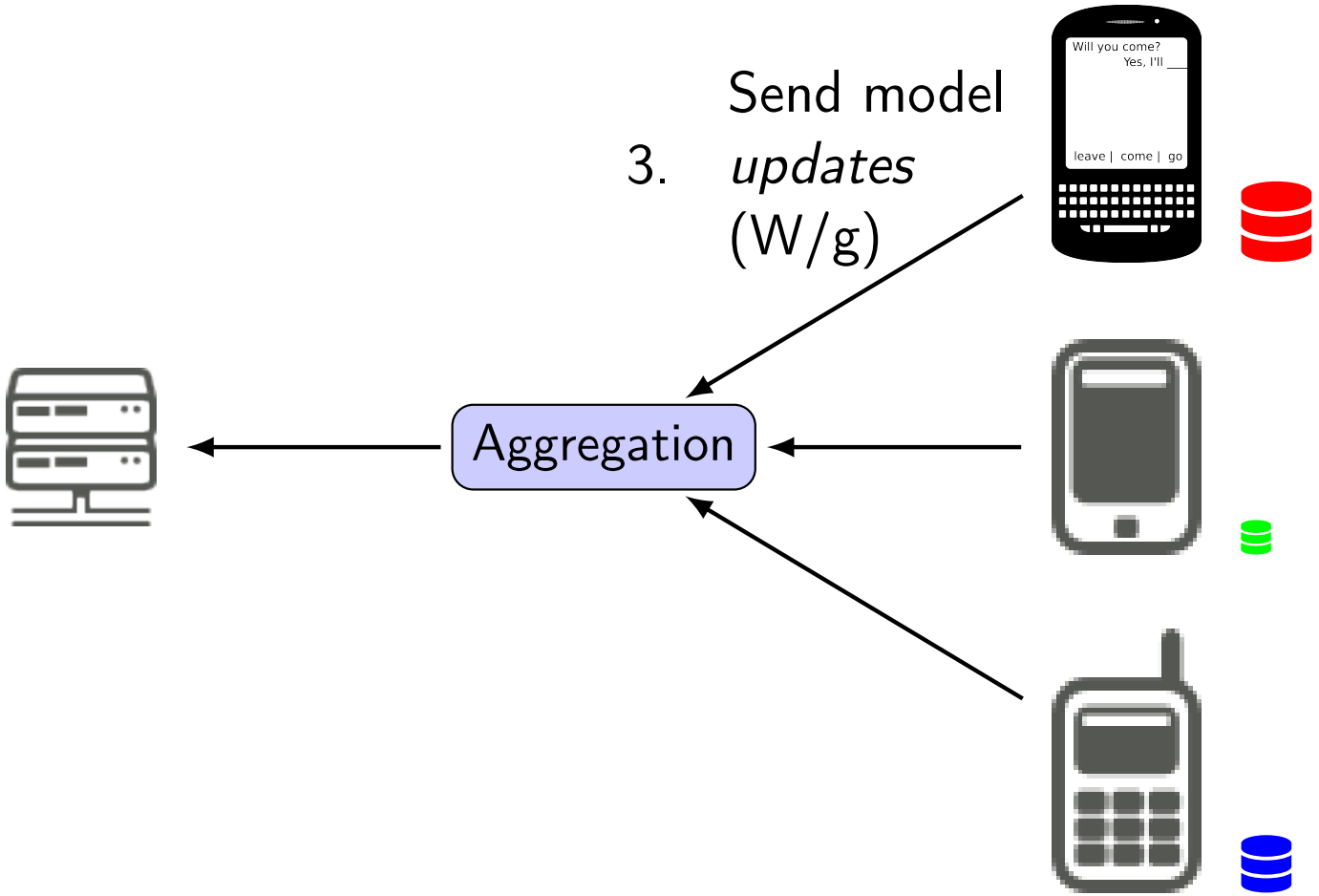
Federated Learning – Principle



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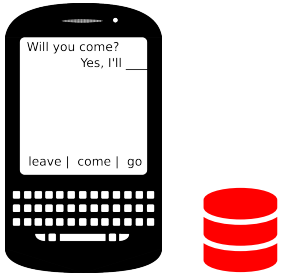
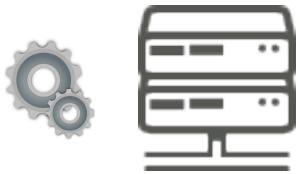
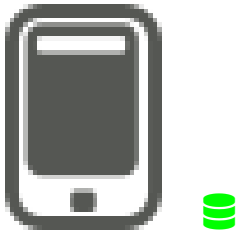


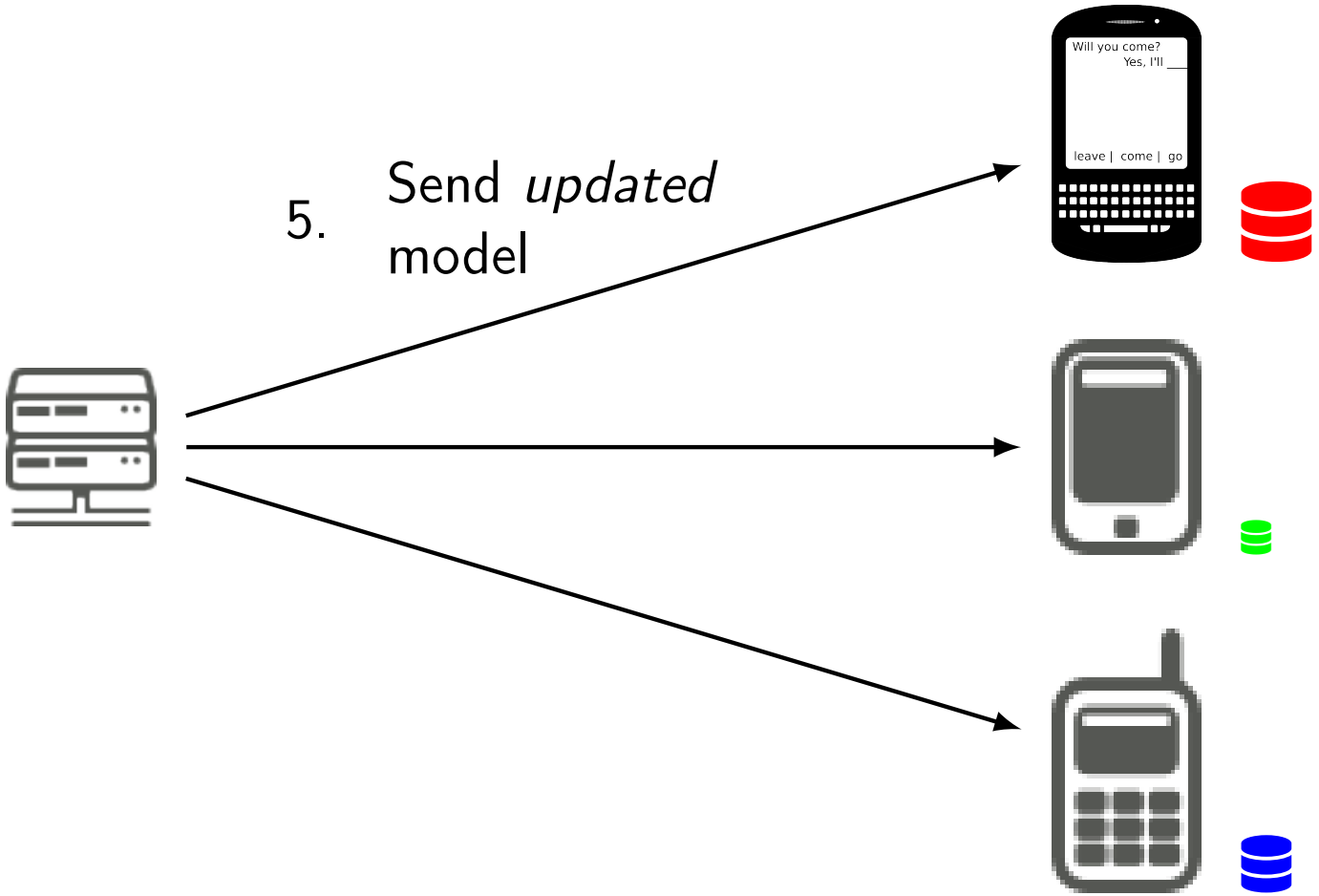




4. Update *global* model

Based on: H.B. McMahan *et al* (2017)

Federated Learning – Principle



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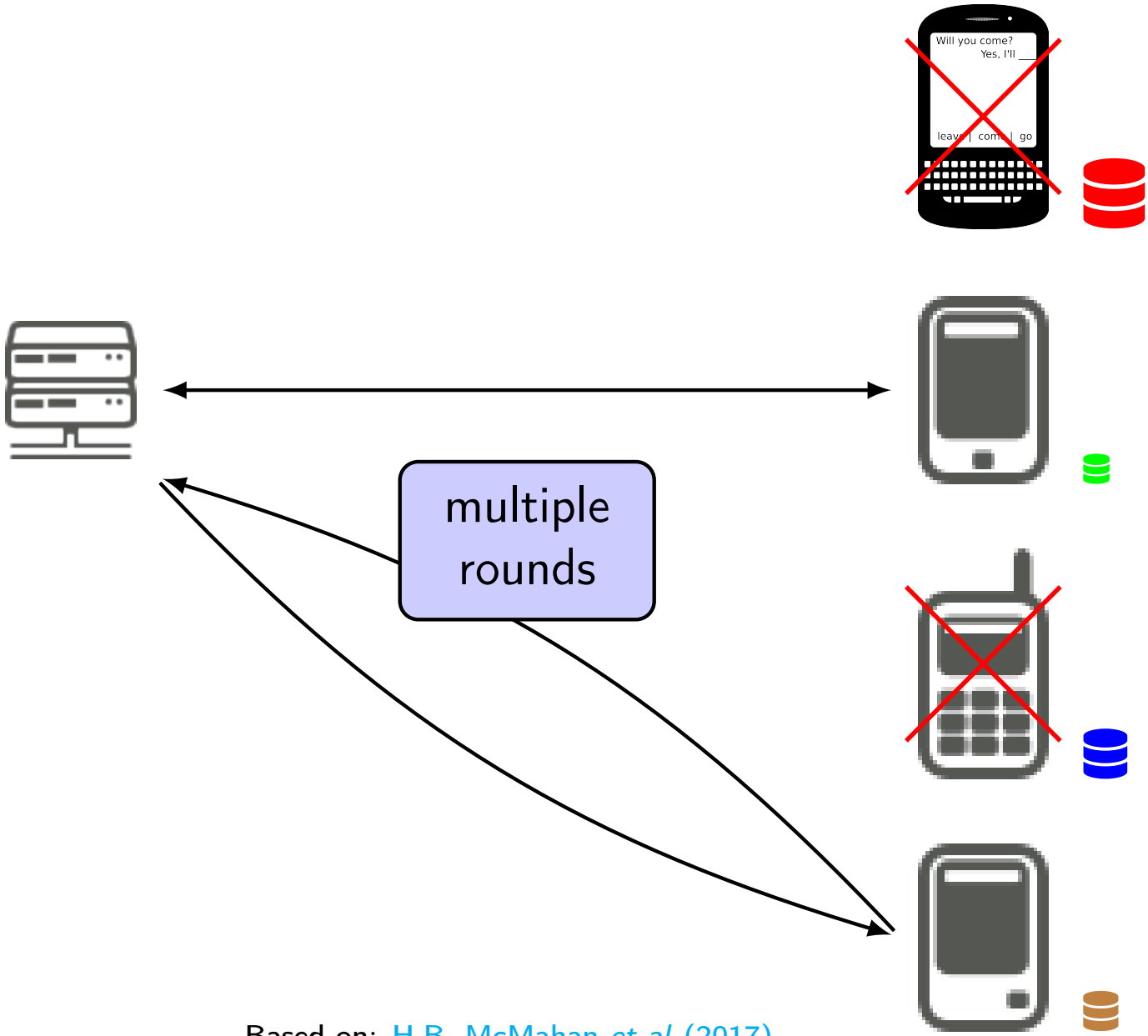
Federated Learning – Principle



Based on: H.B. McMahan *et al* (2017)

Federated Learning – Pros & Cons

Pros

- **Privacy**
  - model updates = unreadable (Weights/Gradients)*
- **Efficiency**
  - **CPU**: distributed computing**
  - **Net**: `size(raw data)` $\ggg$ `size(model updates)`***

Cons

Practice works!****

Theory still research to do on *many* aspects!

Outline

Privacy Problem in Standard FL

Model Inversion (M. Fredrikson *et al*, 2015)

Privacy Problem in Standard FL

Model Inversion (M. Fredrikson *et al*, 2015)

Privacy Problem in Standard FL

Model Inversion (M. Fredrikson *et al*, 2015)

Model Inversion (B. Hitaj *et al*, 2017)

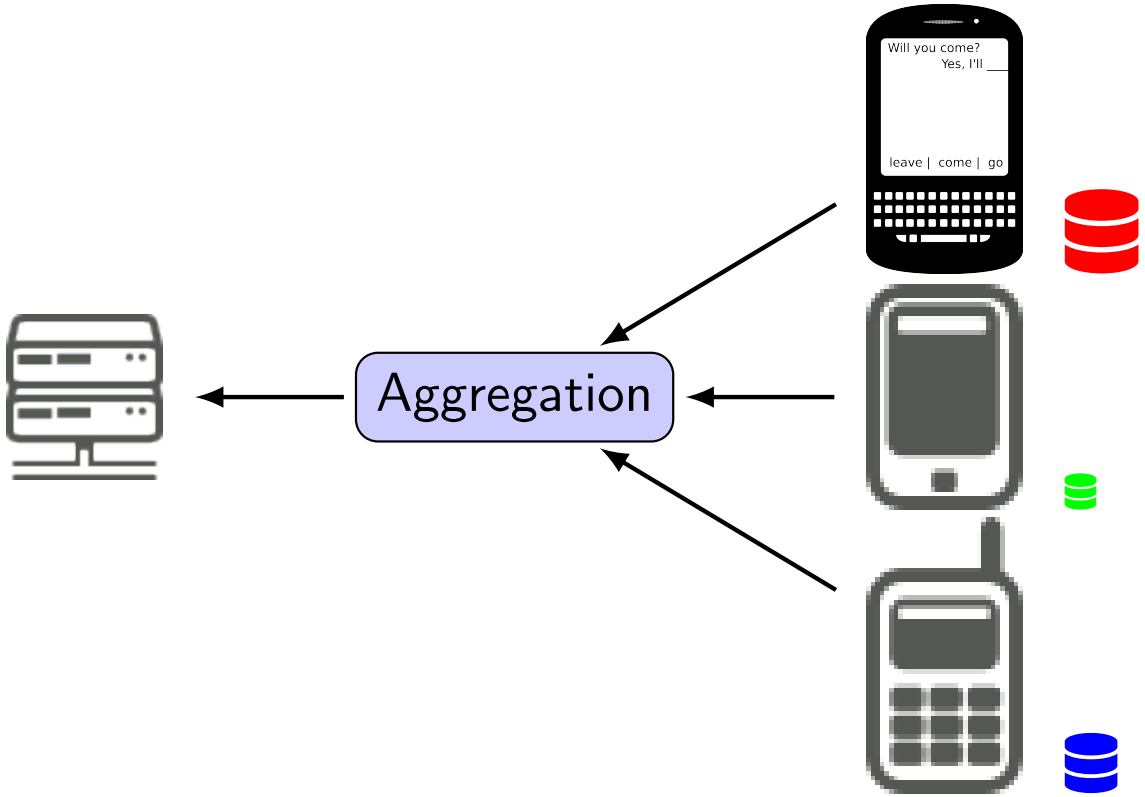
Original

$\theta_u = 1$
$\theta_d = 1$

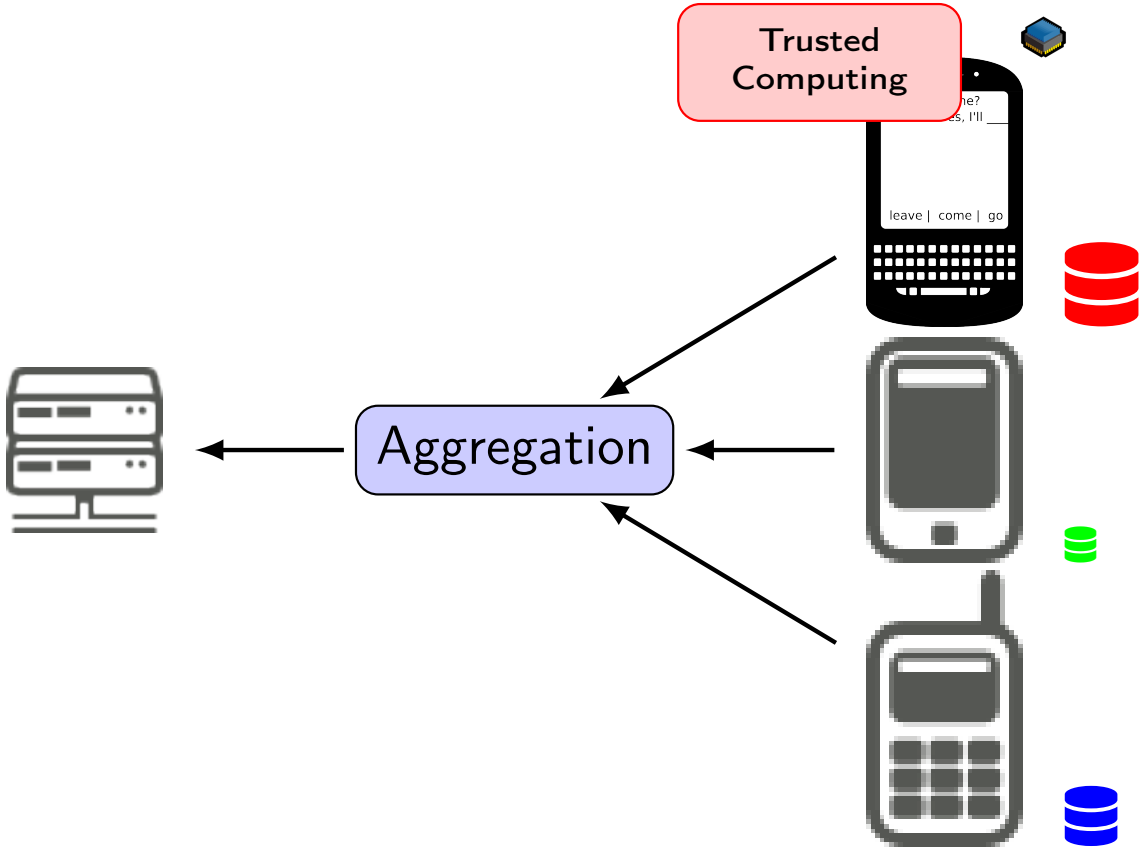
$\theta_u = 0.1$
$\theta_d = 1$

$\theta_u = 0.1$
$\theta_d = 0.1$

Protecting Privacy in FL (Based on: C. Wierzynski)



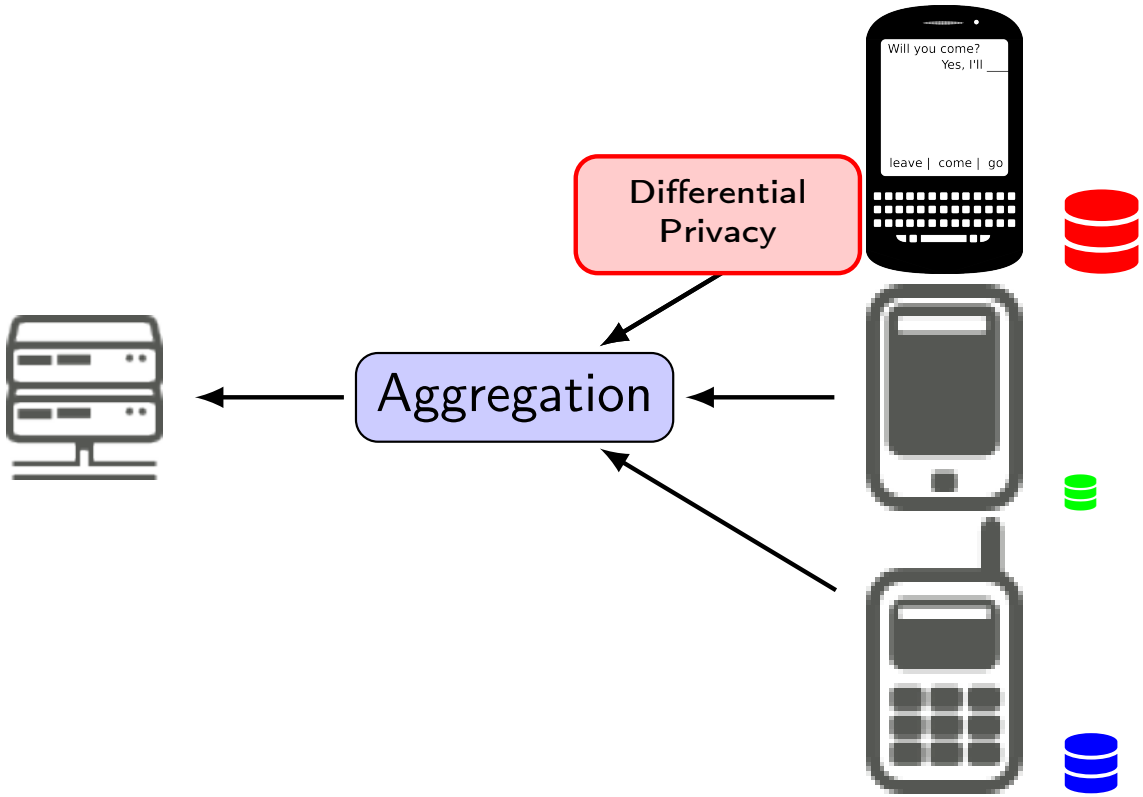
Protecting Privacy in FL (Based on: C. Wierzynski)



Trusted Execution Environment (TEE)

- Prevents external processes from reading RAM
  - Raw Data, Model, Gradients...
- Hardware protection (Intel, AMD, ARM, RISC-V...)

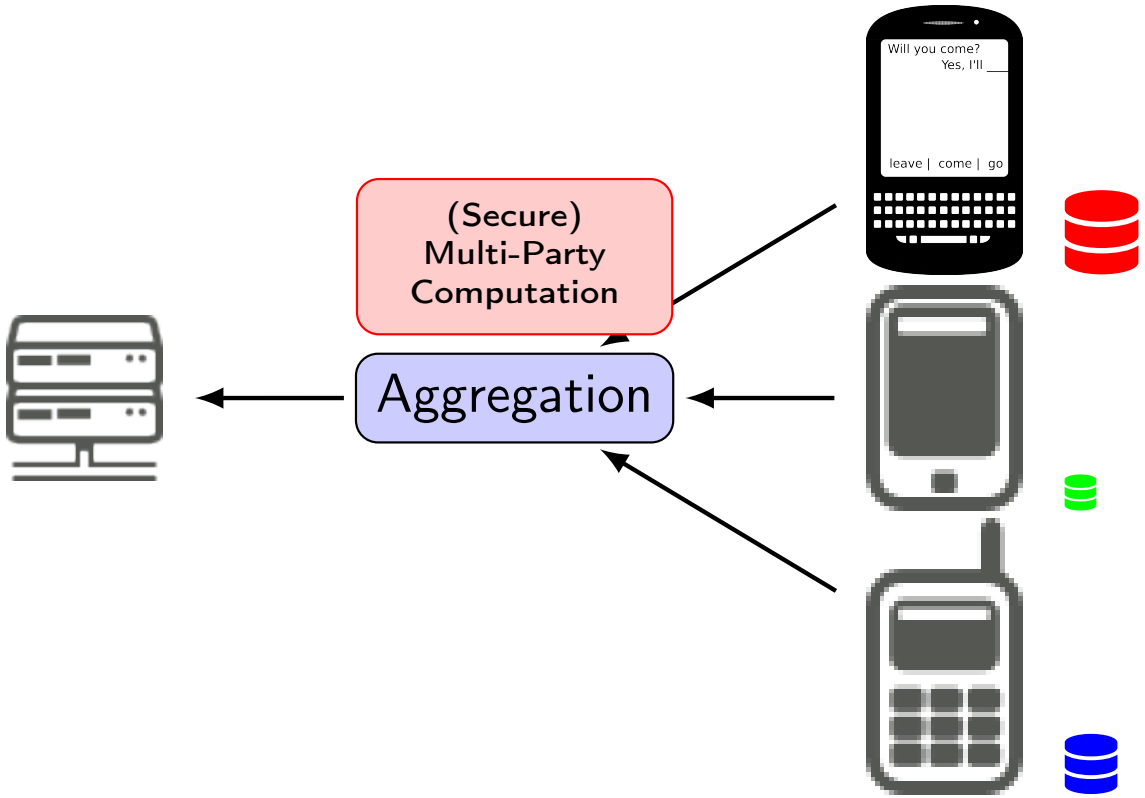
Protecting Privacy in FL (Based on: C. Wierzynski)



Differential Privacy (DP), (C. Dwork *et al*, 2014)

- Add noise to dataset so that stats remain same ⇒ ML possible
  - Limited Bugdet
- Limits "Model Inversion" attacks

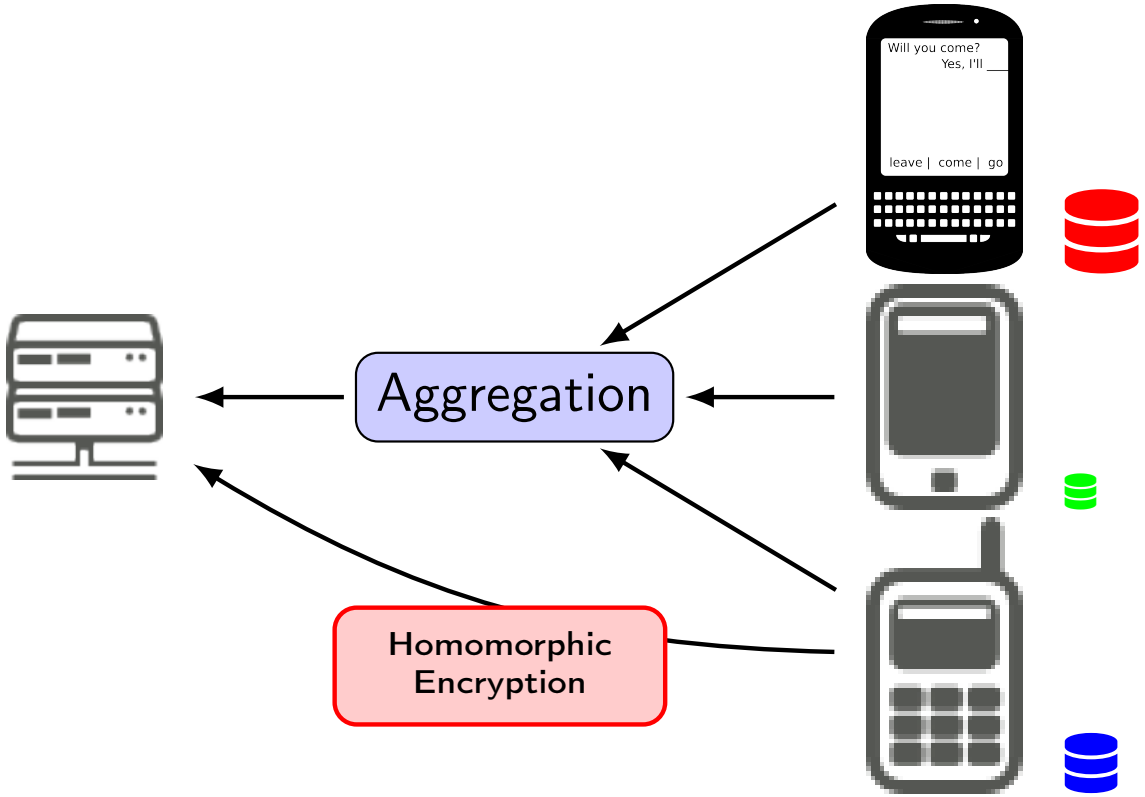
Protecting Privacy in FL (Based on: C. Wierzynski)



(Secure) Multi-Party Computation ([S]MPC)

- Jointly compute a function while keeping inputs private
  - $(\mathcal{A} + x) + (\mathcal{B} + y) + (\mathcal{C} + z) = (\mathcal{S} - s), s = x + y + z$
- Protects from network eavesdroppers (MitM)

Protecting Privacy in FL (Based on: C. Wierzynski)



Homomorphic Encryption (FEH) (C. Gentry, 2009)

- Compute directly on cyphered data
- Similar technology as SMPC
- 🏆, but order of magnitude less efficient

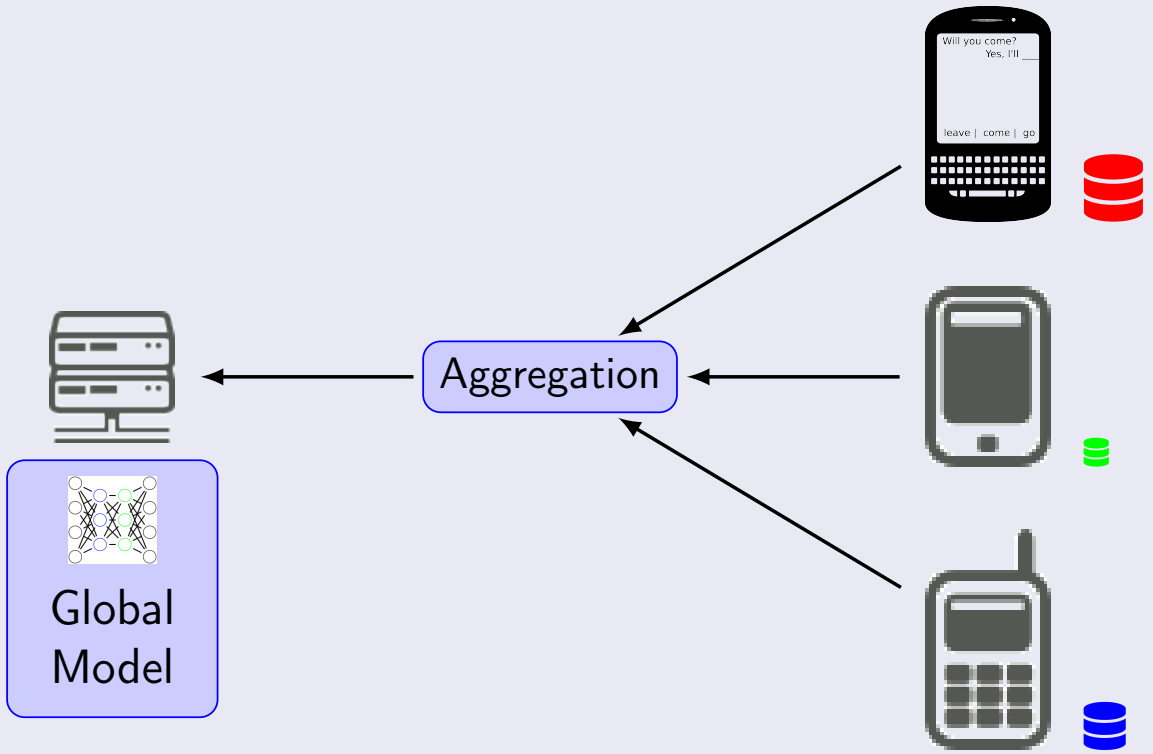
Outline

Federated Learning – Research areas

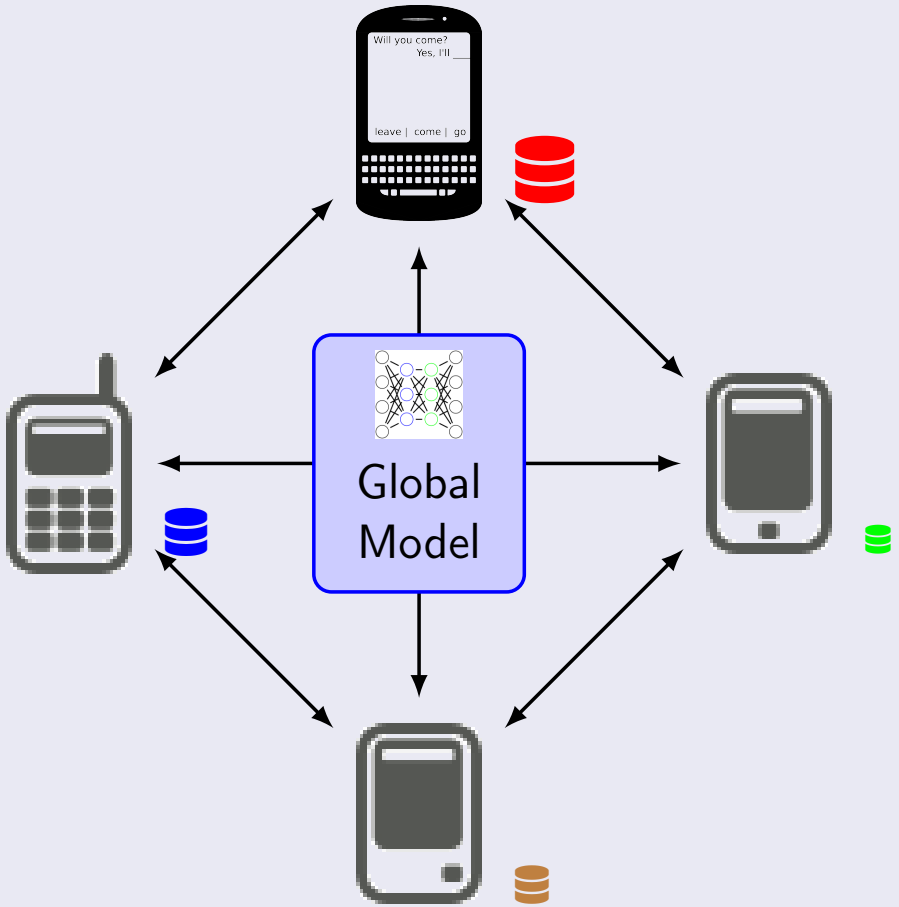
Sources

- Kairouz *et al* (2019) (105p)
- Beutel *et al* (2020) (platforms)
- Khan *et al* (2021) (IoT)

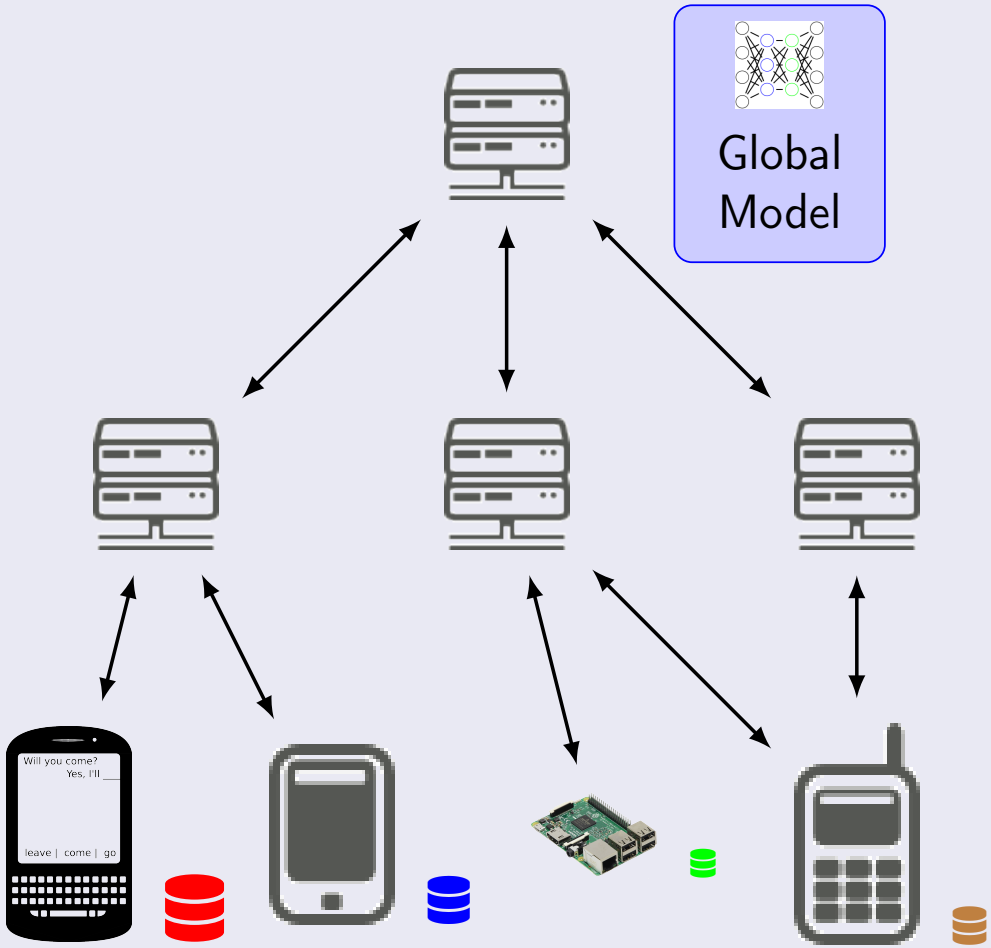
Centralized



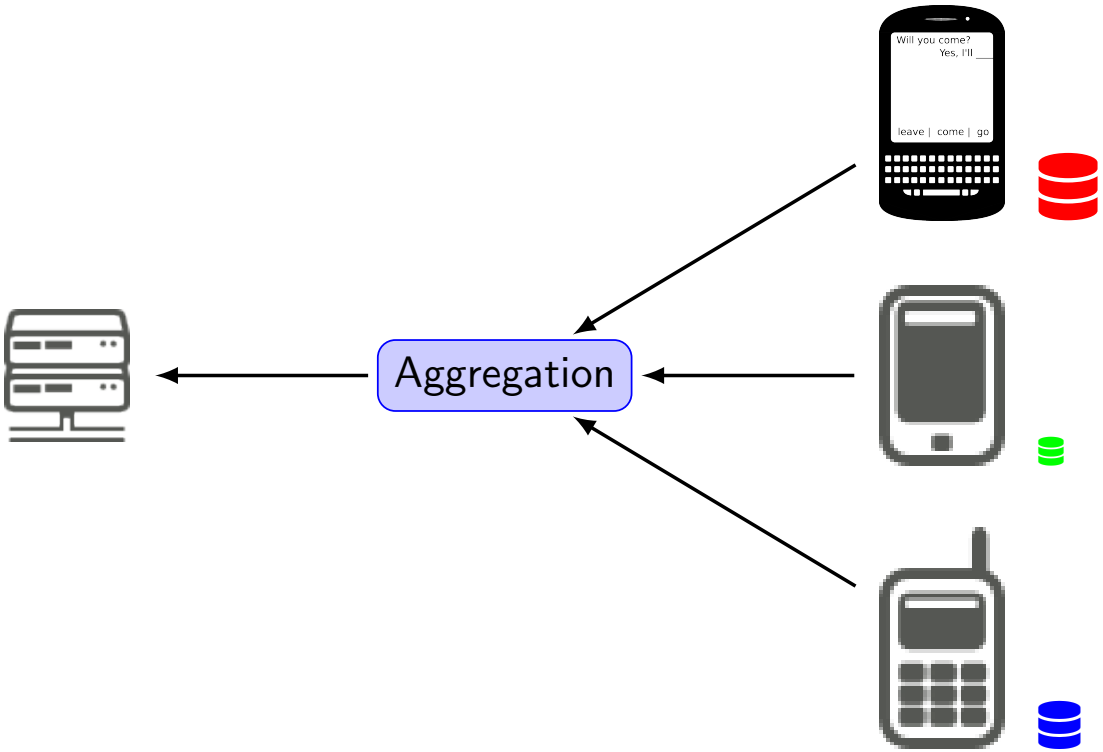
Decentralized



Hybrid

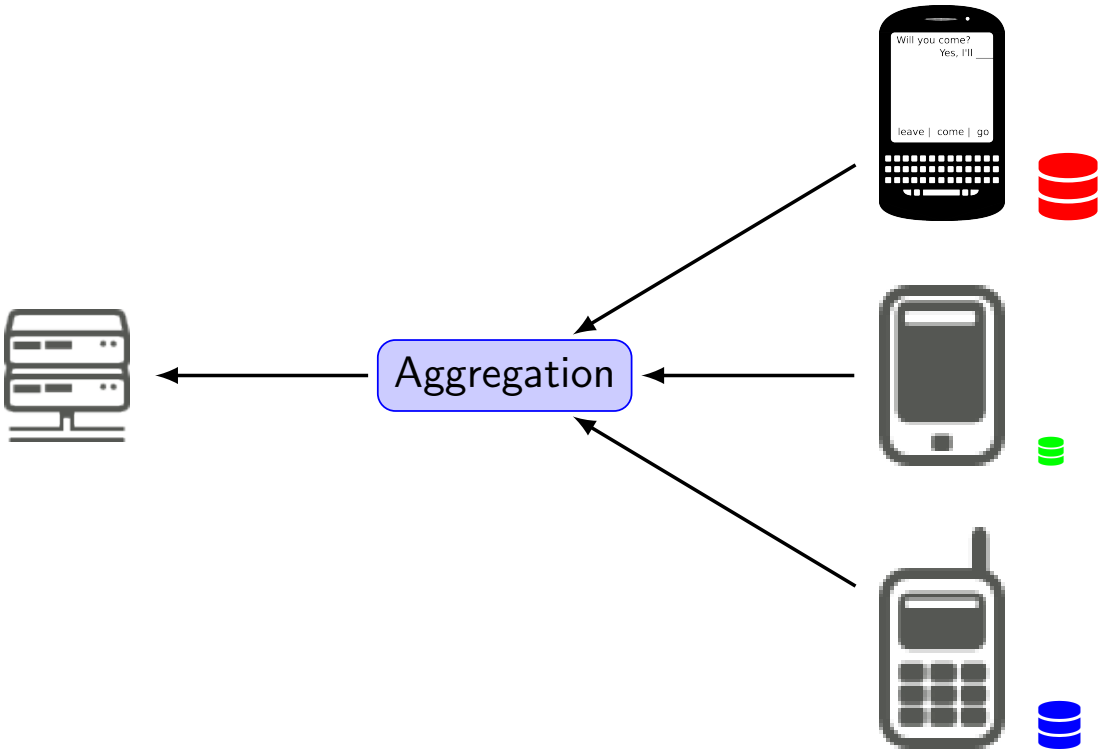


Federated Learning – Research areas

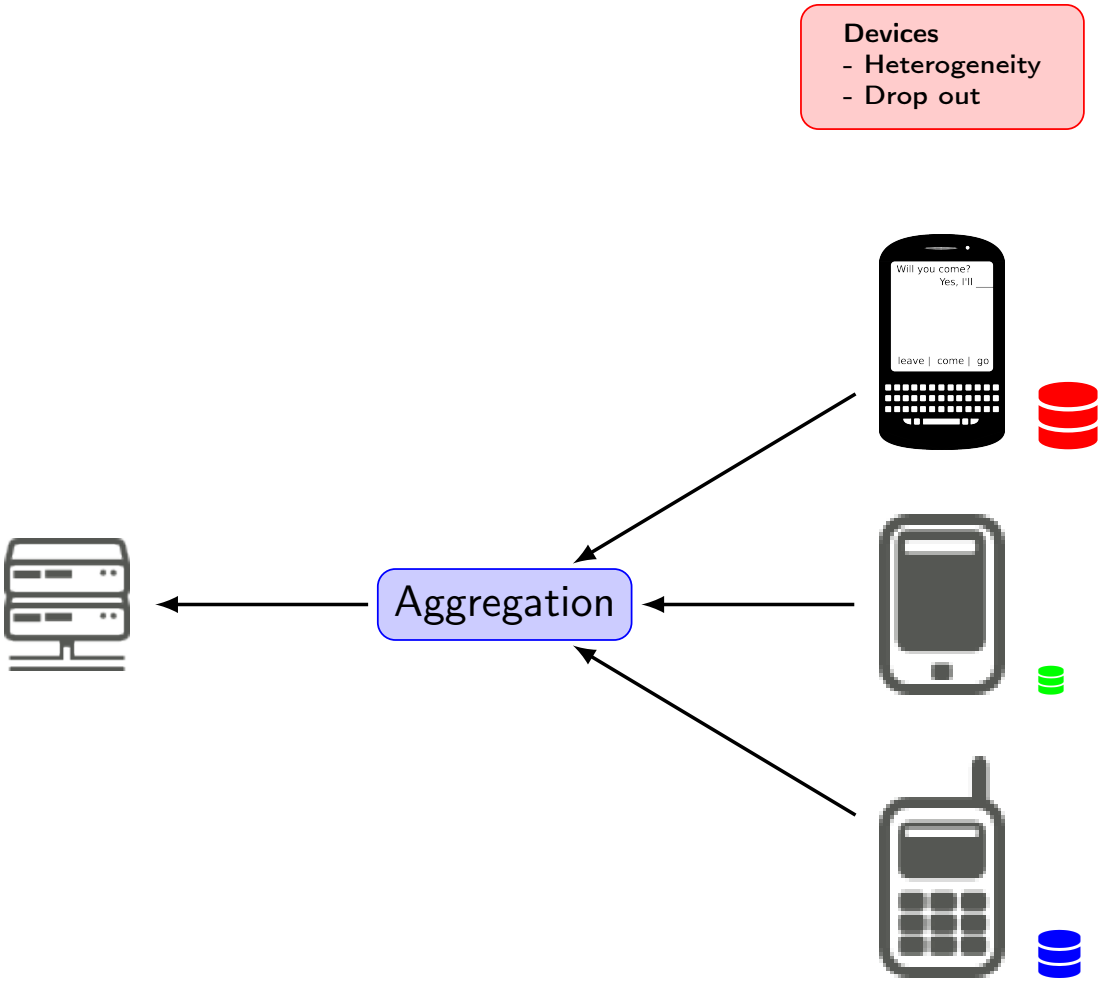


Federated Learning – Research areas

Players
- Cooperative
- Competitive
- Incentive to participate



Federated Learning – Research areas



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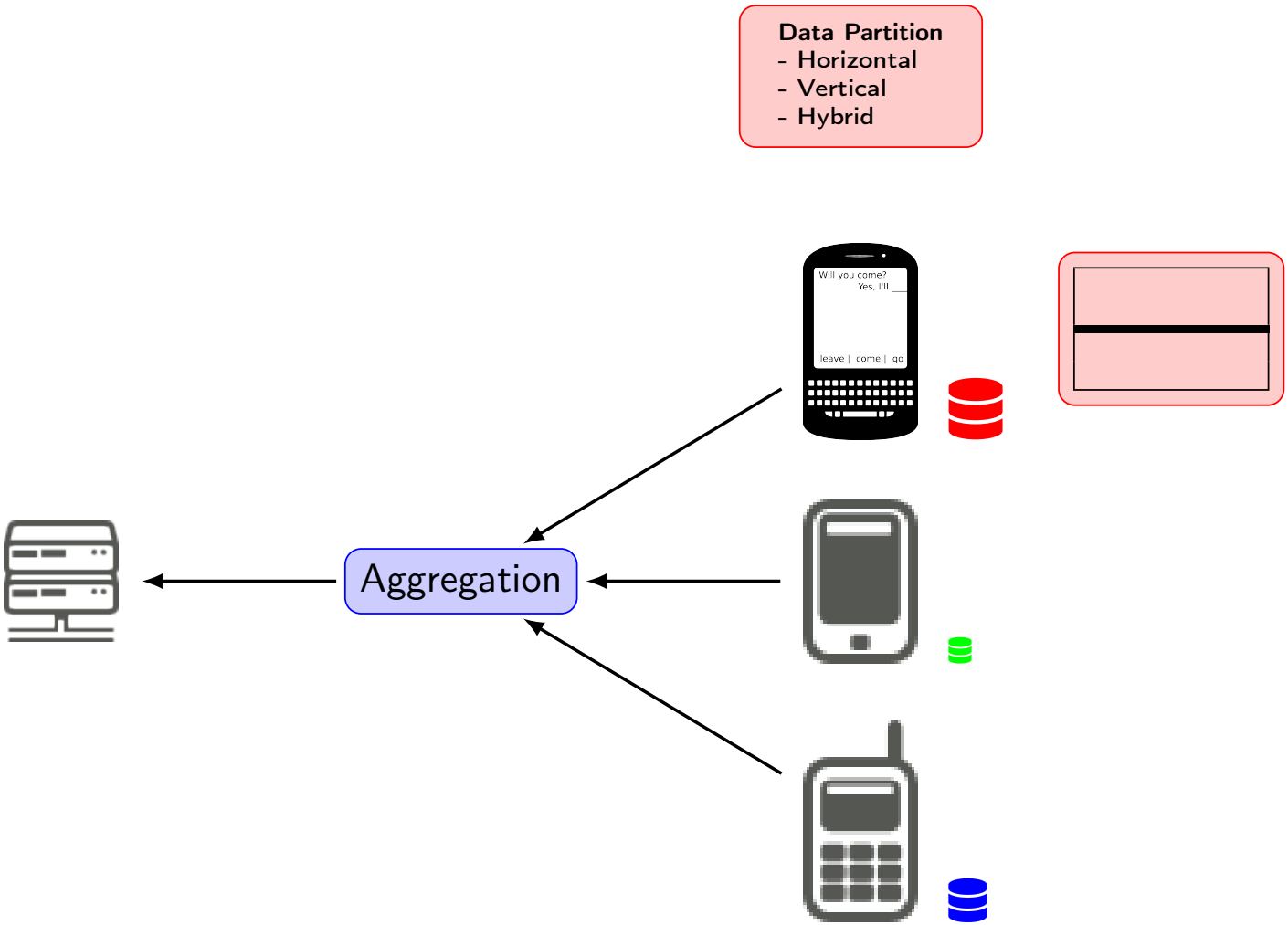
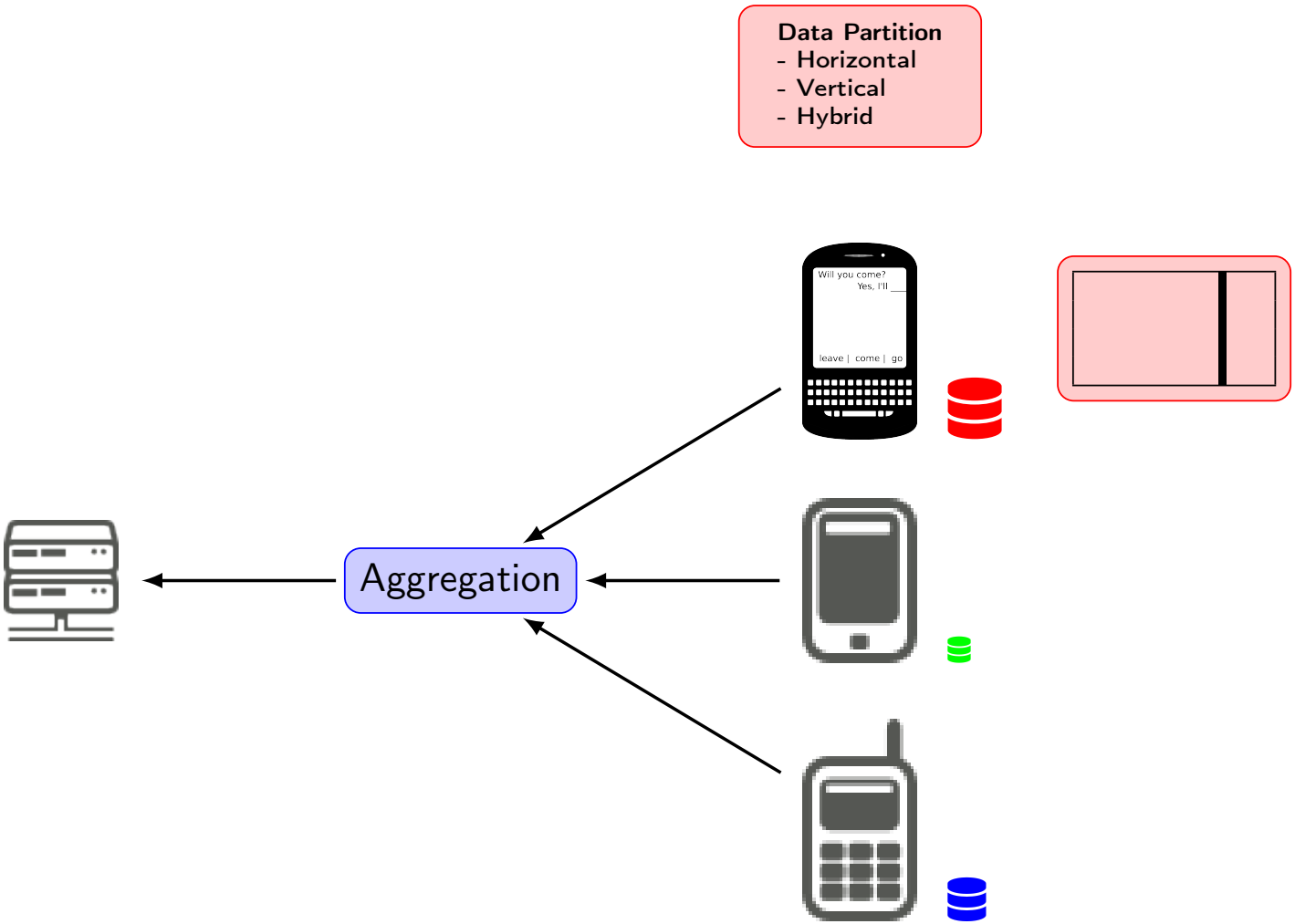
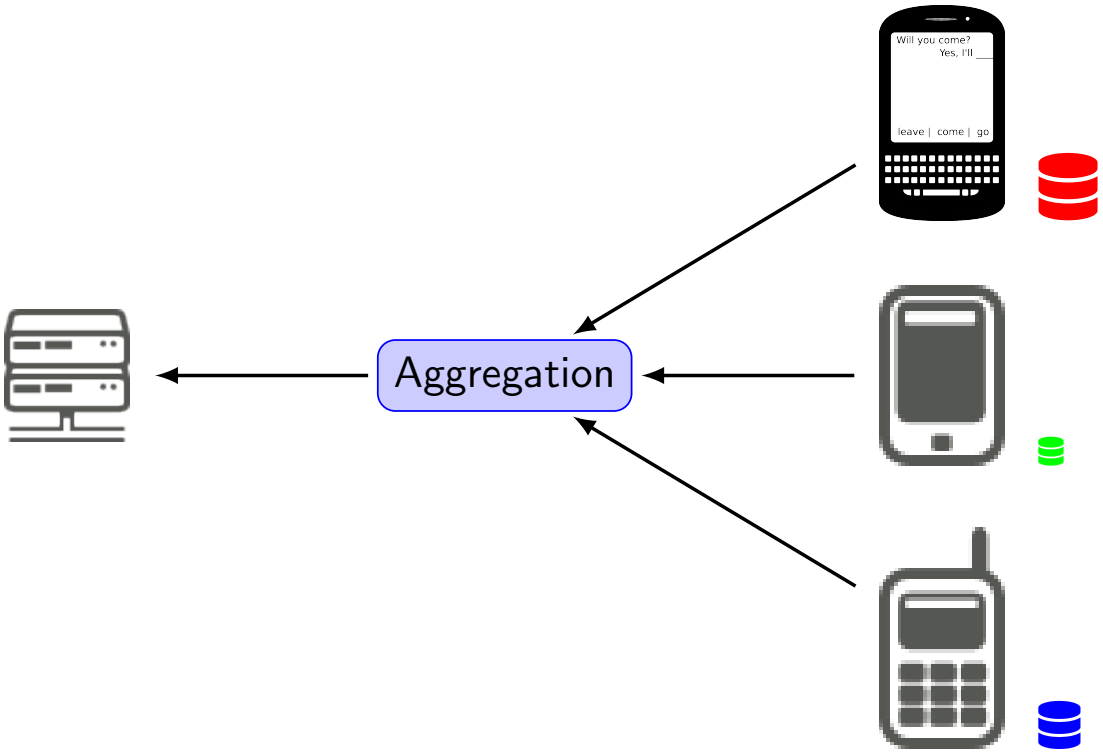


Federated Learning – Research areas

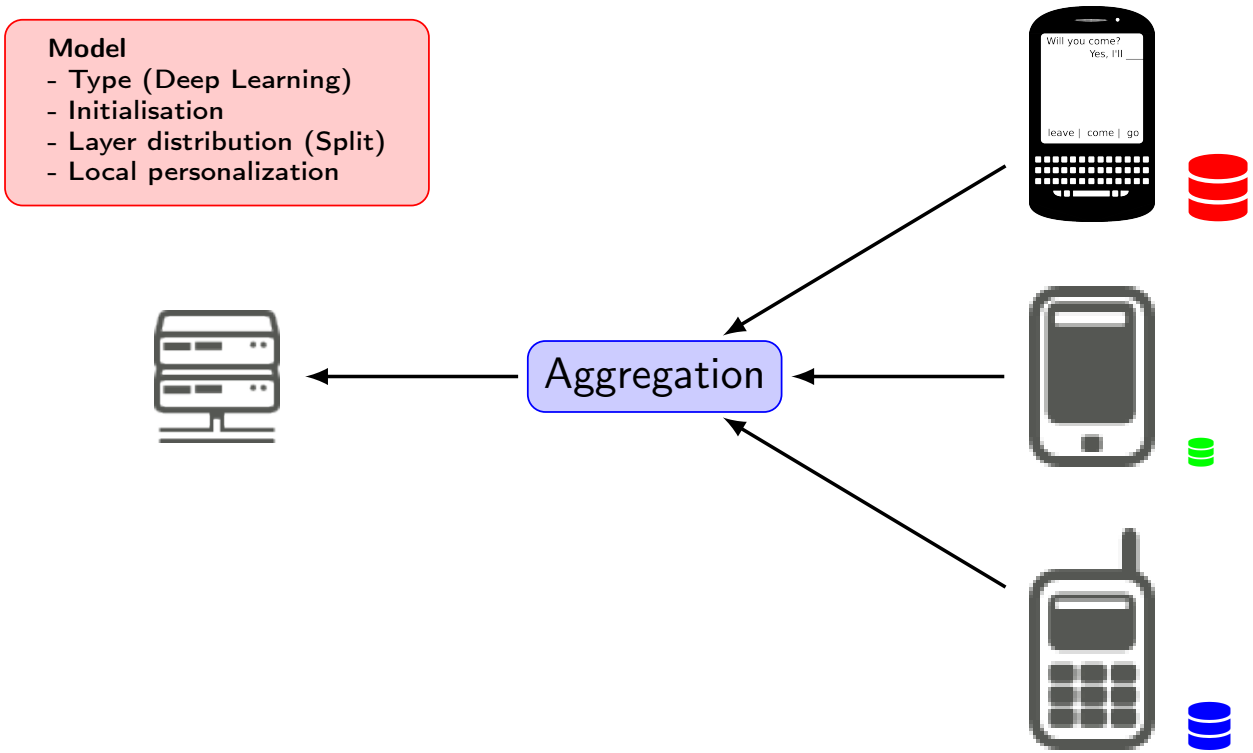


Federated Learning – Research areas

Data Distribution (non/IID)
- im/balance
- in/dependence
- label/feature shifts...



Federated Learning – Research areas



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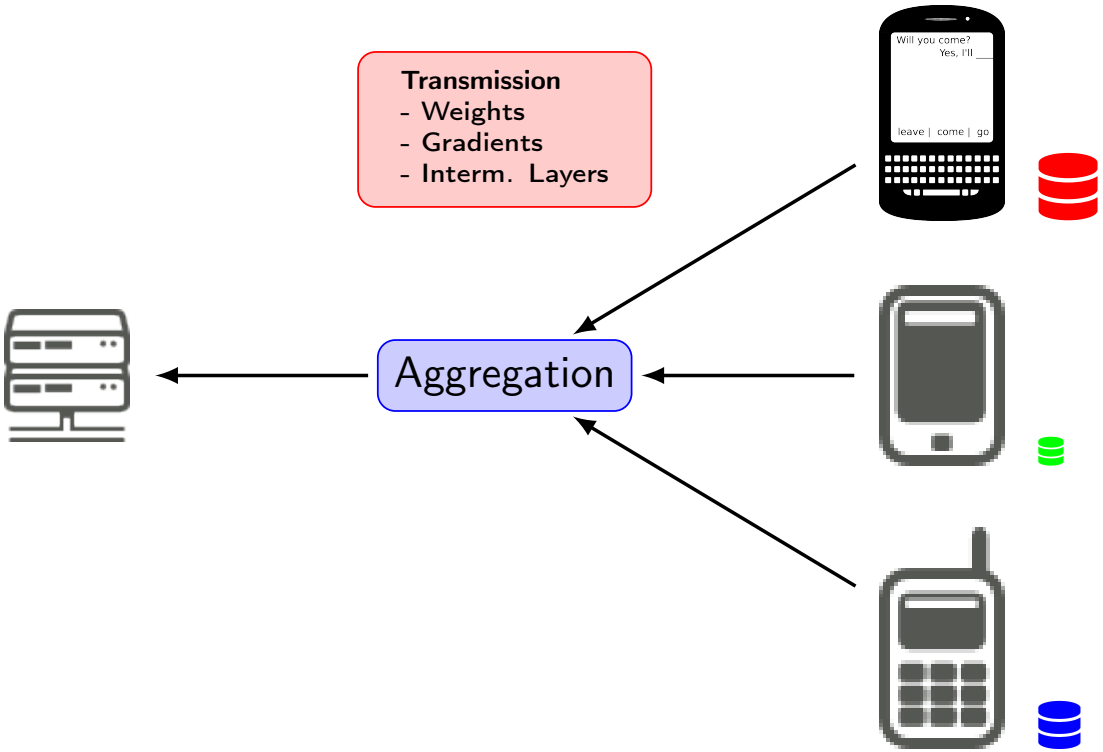

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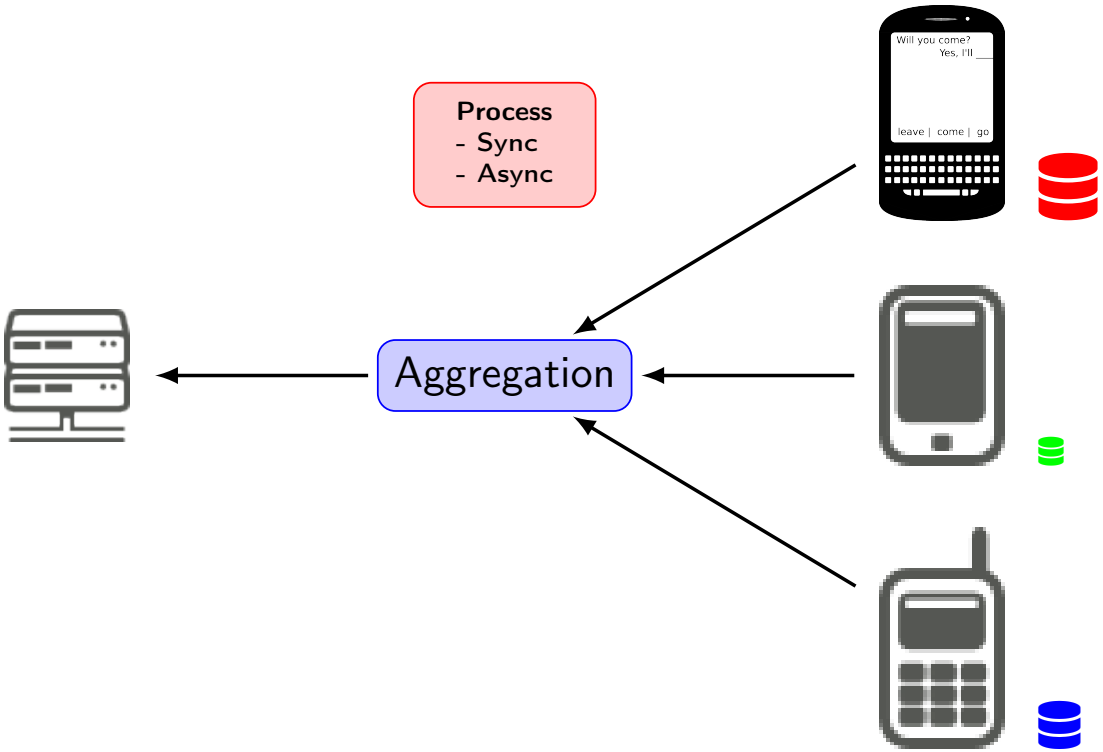

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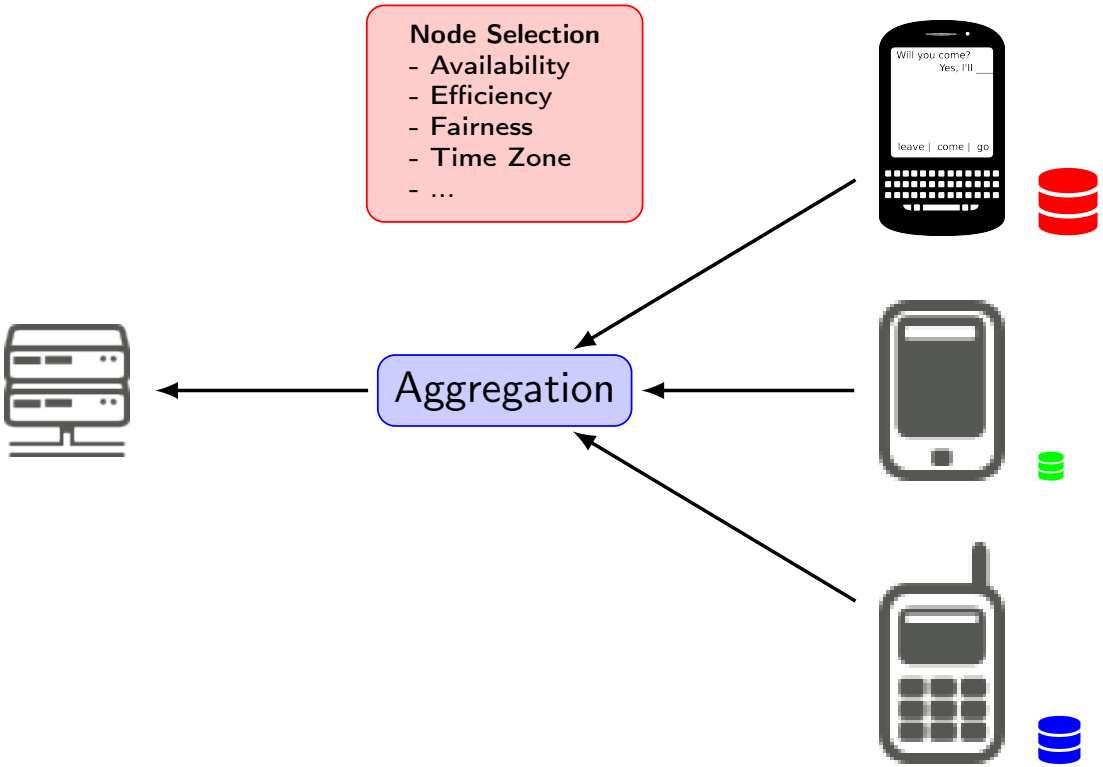
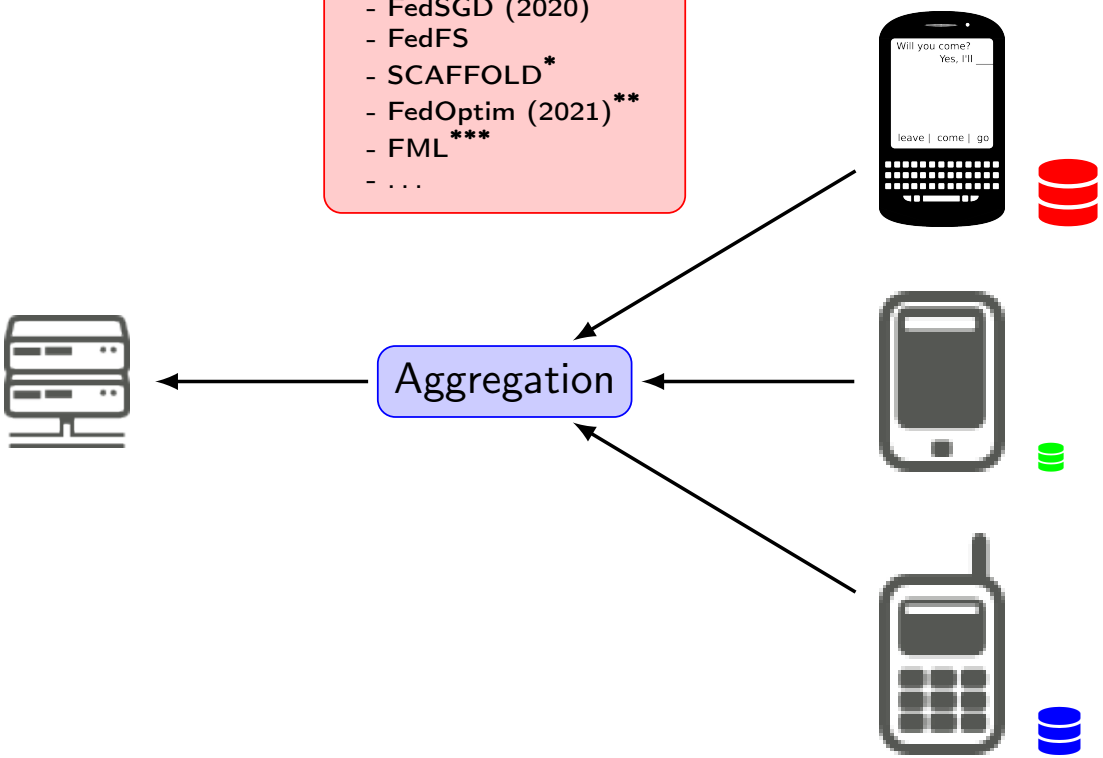


Federated Learning – Research areas

Averaging
- FedAVG (2017)
- SecAgg
- FedProx (2018)
- MATCHA (2019)
- FedSGD (2020)
- FedFS
- SCAFFOLD*
- FedOptim (2021)**
- FML***
- ...



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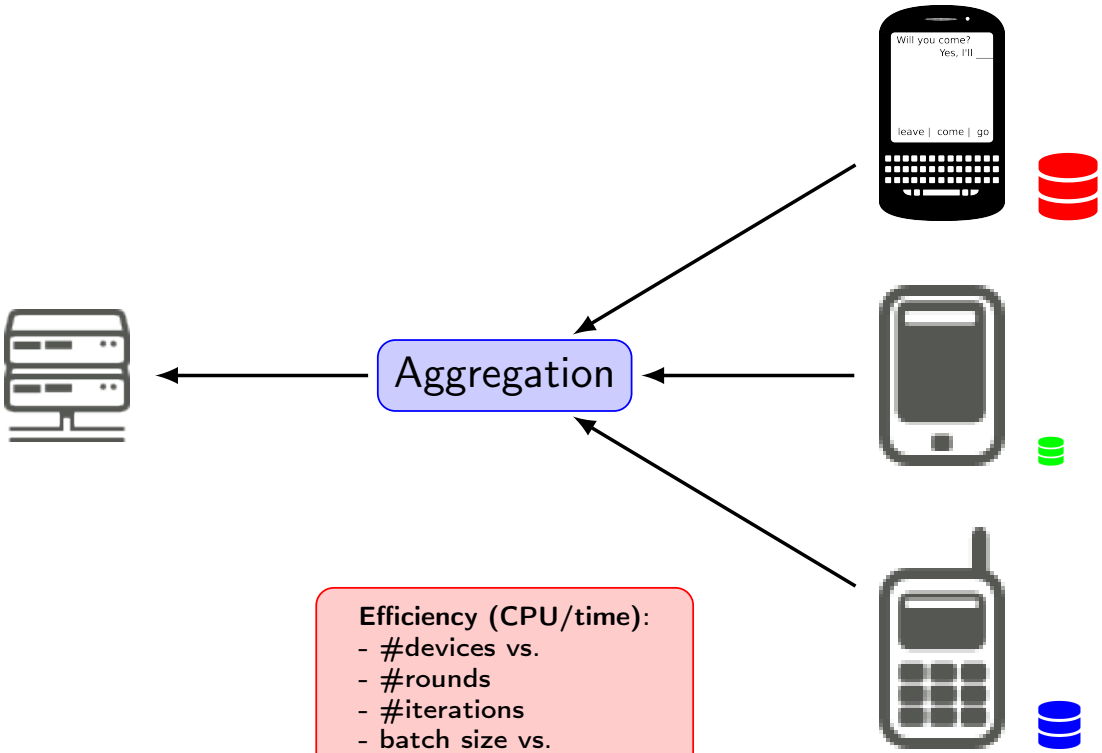
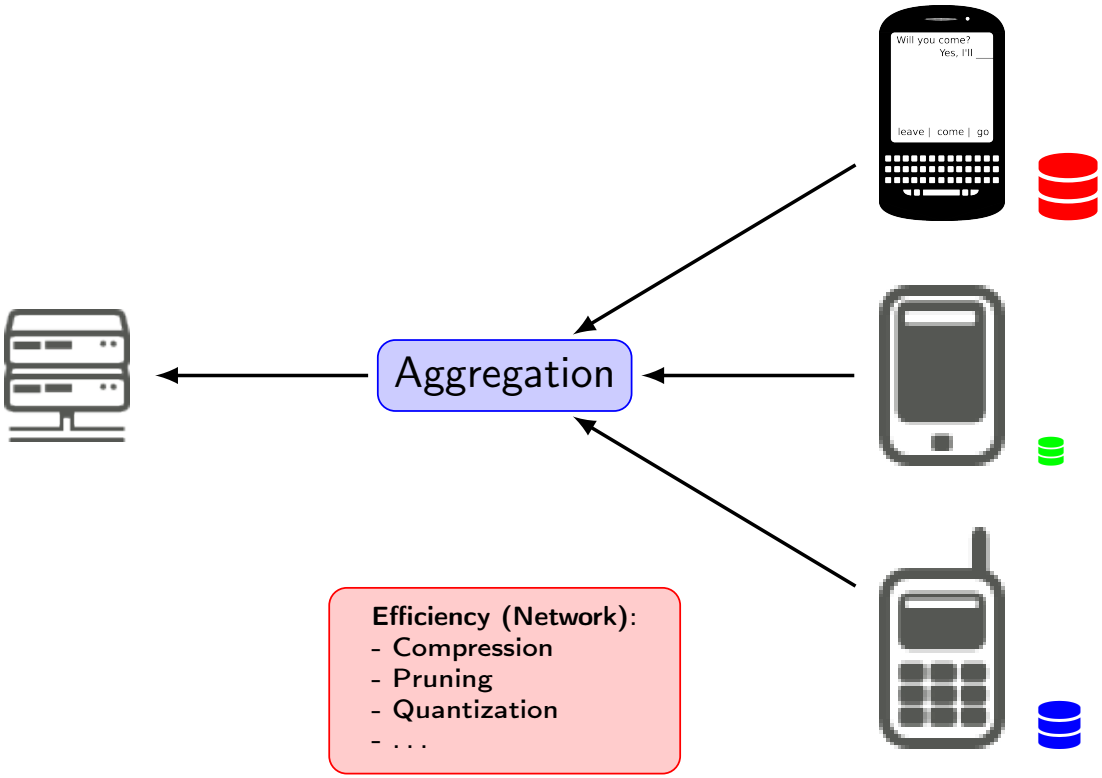


Efficiency (CPU/time):
- #devices vs.
- #rounds
- #iterations
- batch size vs.
- convergence time vs.
- accuracy vs.
- ...

Federated Learning – Research areas



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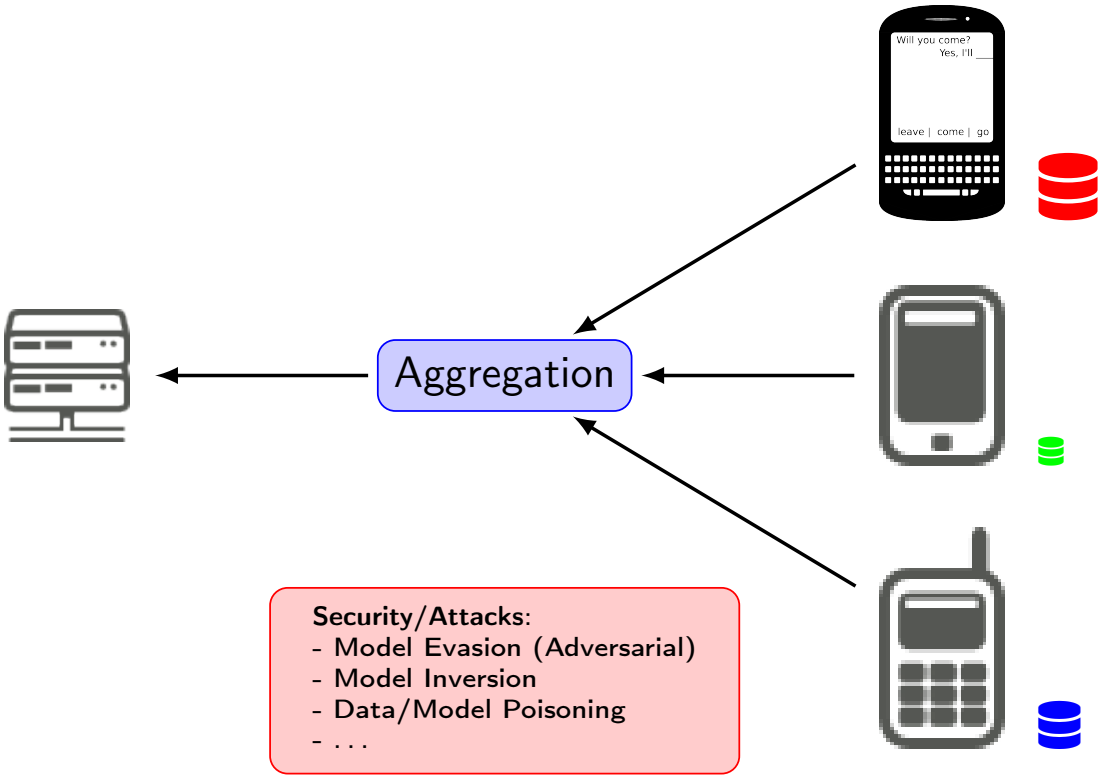

Outline

A lot of platforms!!!

Big Players – "Red Hot"

- PySyft (OpenMined)
- Tensor Flow Federated (Google)

Big Players – "Industrial"

- FATE (WeBank)
- IBM-FL (IBM)
- CLARA (NVIDIA)
- Open Federated Learning (Intel)
- PaddleFL (Baidu)
- Owkin Connect (Owkin)

Big Players – "Academic"

- FedML (USC)
- LEAF (Carnegie Mellon)
- Flower (UK, DE, FR)

Others

- XayNet
- G(alaxy)FL
- Sherpa.ai
- DiscreetAI

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- Sherpa.ai
- DiscreetAI

PySyft

https://github.com/OpenMined/PySyft

Who

- OpenMined (Andrew Trask)

What

- Low level
- Central Controller
- PyTorch & TensorFlow

Focus

- Privacy

Pros

- Lots of docs

https://www.youtube.com/watch?v=NJBBE_SN90A (commercial)
https://www.youtube.com/watch?v=4zrU54VIK6k (technical)

Tensor Flow Federated (TFF)

https://www.tensorflow.org/federated

Who

- Google (Krzysztof Ostrowski, Emily Ganz)

What

- Low level
- TensorFlow only

Focus

- Privacy (GBoard)

Pros

- Lots of docs

https://www.youtube.com/watch?v=m17IgaHaoTI

Owkin

https://owkin.com/platform/software-stack/

Who

- Owkin (French startup, Thomas Clozel)

What

- Totally decentralized
- Uses & Ledger/BlockChain (↓ cheating & computation)

Focus

- Health Care Applications
- Vertical FL

Cons

- Only core is FLOSS ("Substra")

https://www.youtube.com/watch?v=mjqTpahgkGs

FedML

https://github.com/FedML-AI/FedML

Who

- Consortium
  - Academics: USC + Stanford + MIT + MSU...
  - Companies: Tencent + WeBank...
- Presented @NeurIPS in dec. 2020

What

- Simulation & On-device
- Device/Platform/Framework Agnostic

https://arxiv.org/abs/2007.13518

Flower

https://flower.dev/

Who

- Consortium (UK + Germany + France...)

What

- Simulation & On-device
- Device/Platform/Framework Agnostic
  - PyTorch, TensorFlow, MXNet...
  - IoT, Servers...

https://arxiv.org/abs/2007.14390

Machine Learning at Laboratoire Hubert Curien

ML ("Data Intelligence" Team)

- Transfer Learning/DA, PAC Bayesian, Graph NN, Fairness...

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  - Interpretability
  - Safety

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- ⚠ PhD/post-doc positions ⚠

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FL & Small Devices (GM + V. Fresse + Telecom Bretagne)

- FPGAs + Split Learning

FL & Privacy (T.N. Le, A. Habrard, M. Sebban)

- Random Projections

Take aways

IoT & AI for Smart Cities

- Smart Applications $\Rightarrow$ Machine Learning
  -  &
  

Take aways

IoT & AI for Smart Cities

- Smart Applications ⇒ Machine Learning
  -  & 

IoT = Decentralized setup / Constrained resources

- Ensure Privacy & Efficiency ⇒ Federated Learning

Take aways

IoT & AI for Smart Cities

- Smart Applications ⇒ Machine Learning
  -  & 

IoT = Decentralized setup / Constrained resources

- Ensure Privacy & Efficiency ⇒ Federated Learning

Federated Learning works!

- There are many platforms
- But there are still challenges in many specific points

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IoT/FL in practice

Preliminaries

- `apt install python3`

Virtual Env

- `apt install python3-venv`
- `python -m venv isc2lab && cd isc2lab && . ./bin/activate`

FL Platform: Flower + ML lib: TensorFlow

- `pip3 install flwr`
- `pip3 install tensorflow`

Code & Dataset

- https://github.com/GMTSE/isc2-IoT-AI-smart-tutorial