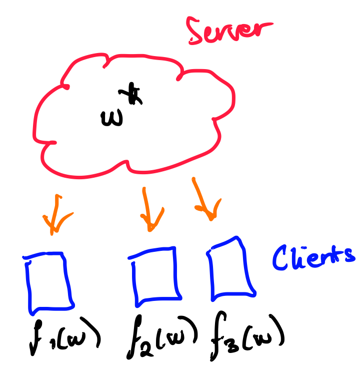
Background

Personalised FL

- Traditional FL:
  - Train a centralised model that performs well on average



$$\min_{w \in \mathbb{R}} f(w) := \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$ Same model

$$f_i(w) := \mathbb{E}_{(x,y) \sim p_i}[l(w; x, y)]$$

- FedAvg - designed to fit the avg client

Benefits

- Privacy-preserving
- Solves data scarcity

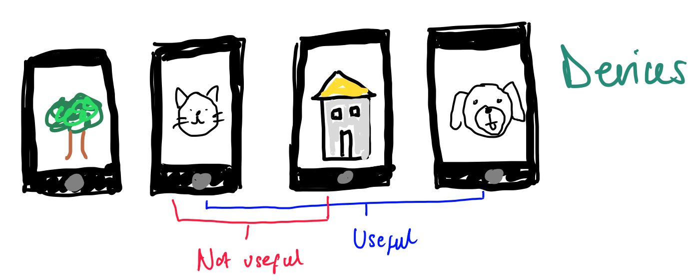
- Aim of P-FL is to strike a balance between a global model that performs well on average, and a personalised model that works very well for a particular client

Why federate?

- Data scarcity
  - Leverage more data from other sources
- Privacy + non-interoperable

Non-I.I.D data

- Data that come from different distributions
- Real-world data is more likely to be non-I.I.D
- Fed Avg struggles with this
- Not all client models are relevant for a particular class



FOMO

- Instead of giving all clients the same global model average weighted by training size - for each client compute a weighted combination of all available models aligned to the clients interests
- FedFO

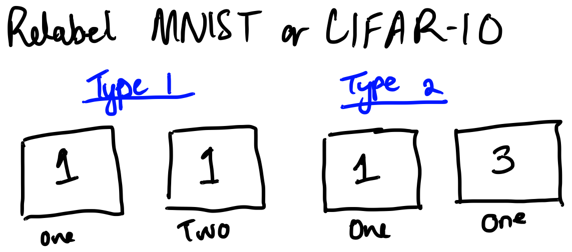
Issues with normal FL

- Non-guaranteed convergence
- Model parameter divergence
- Poor adaptation to local client test sets
- Conflicting weight updates

Plan

Concept drift

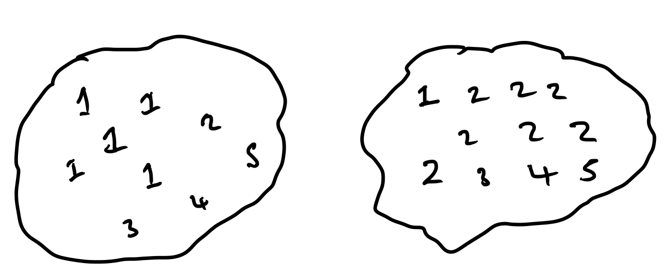
Relabel MNIST or CIFAR-10



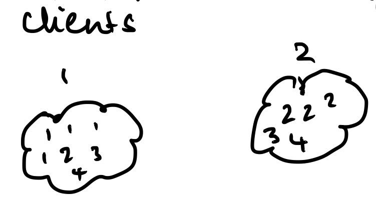
- Randomly corrupt labels
- Percentage chance?

Img	Label	New label
[.......]	0	→ 1
[.......]	5	→ 6

Label distribution skew



- artition labels to specific clients →



Qs

- Randomly distribute samples to clients

↓

Next

- Run training + compare to baseline
- Plot

RESULTS

	QS	LS	CD 0.1	CD 0.25	CD 0.5
Pfedme	0.9200	0.6893		0.7322	0.5092
Pfedme(p)	0.9202	0.7244	0.8907	0.7246	0.5101
perAvg	0.9108	0.7600	0.8944	0.7330	0.5157
FedAvg	0.9203	0.7033	0.8940	0.7334	0.5116