

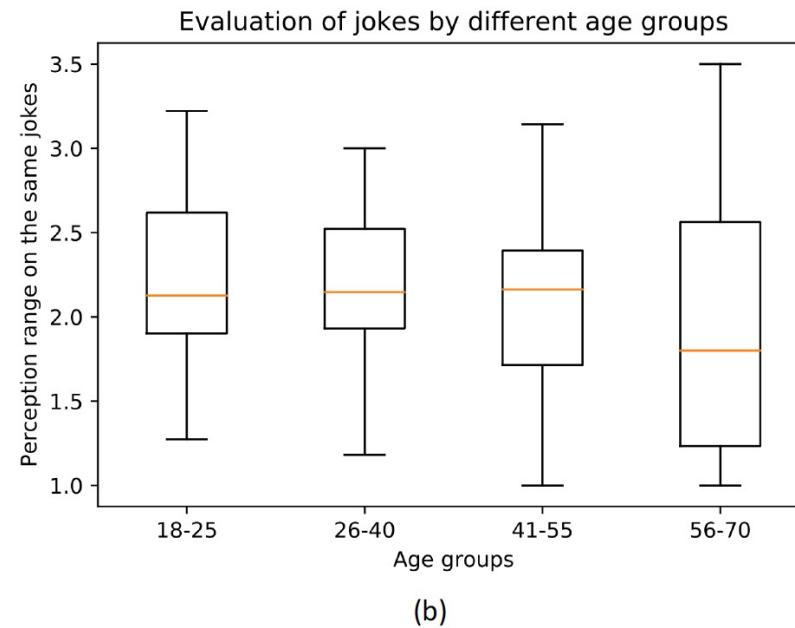
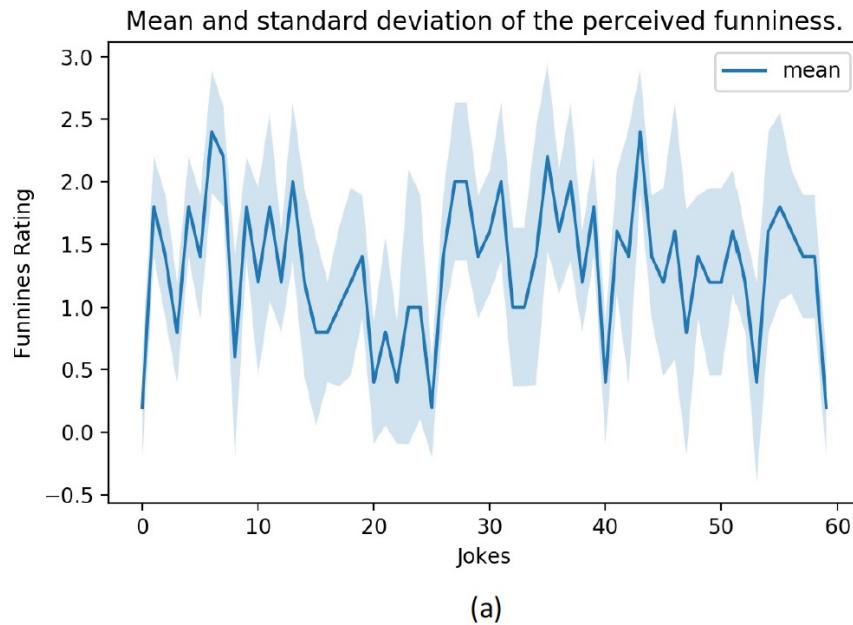
# Federated Learning for Personalized Humor Recognition

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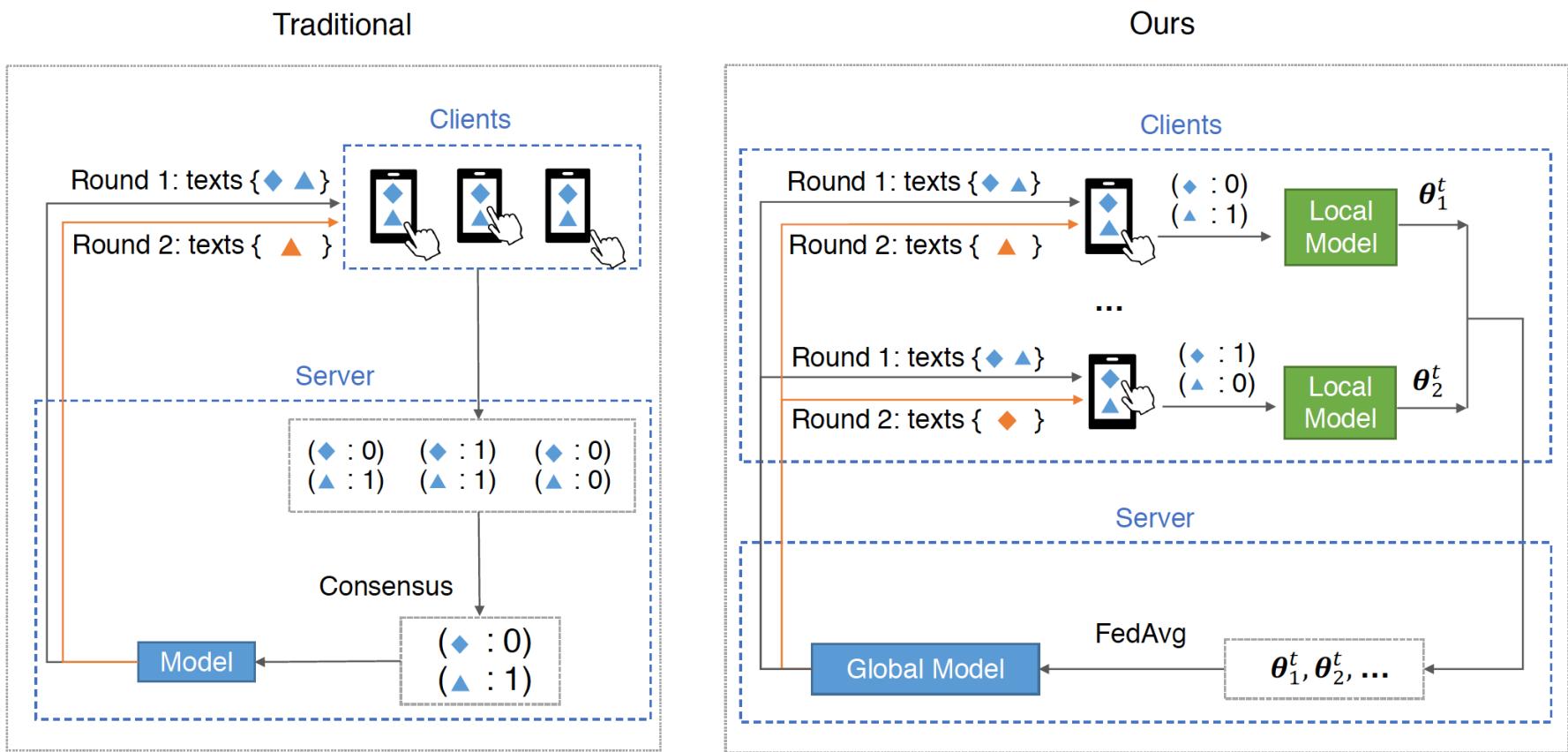
# Background and Motivation

- Human perception of a joke is highly *subjective*
- Observation: every joke can be perceived differently by different people



Data from "President Vows to Cut ~~Taxes~~ Hair": Dataset and Analysis of Creative Text Editing for Humorous Headlines. 2019. In NAACL.

# Personalized humor recognition through federated learning



# Weight-tying Federated Updates

Update  $\theta_i^t$  in regular gradient descent:

$$\theta_i^{t,0} = \theta^t$$

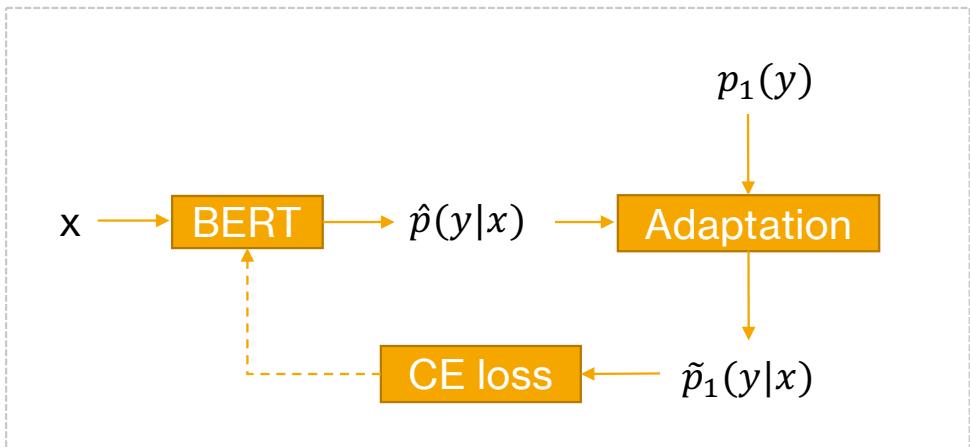
$$\theta_i^{t,K} = \arg \min_{\theta_i^t} L(\theta_i^t; \alpha_i) \quad (5)$$

Weight tying is achieved using federated averaging

$$\theta^{t+1} \leftarrow \frac{1}{m} \sum_{i=1}^m \theta_i^{t,K} \quad (6)$$

Repeat

# Local Adaptation with FedHumor



- Adaptation
  - $\tilde{p}_i(y|x, \alpha_i) = \text{Softmax}\left(\frac{\hat{p}_i(y|x)}{p_i(y)^{\beta_i}}\right)$  (1)
  - $p_i(y)$  is the local empirical label distribution
    - $p_i(y) = \frac{1}{|D|} \sum_j \mathbb{1}(y_{i,j} = \text{funny})$  (2)
  - $\beta_i$  is a hyperparameter determined on validation set.

Objective function:  $L_i(\theta_i^t) = -y_i \log \tilde{p}_i(y|x) + \lambda \|\theta_i^t\|_2^2$  (3)

# Comparison of Different Training Strategies

- Data:
  - Differently and independently distributed
- Training Approach:
  - AGG: *aggregate* all the labelled data and train on a centralized setting.
  - INDV: *individually* train a model for each user.
  - FED: using *federated averaging* to tie weights.
- Testing scenarios:
  - Group 1: a group of 3 users with unique preferences
  - Group 2: a group of 18 users with unique preferences

Table 2: (Average) Test performance

		Precision	Recall	$F_1$ score
Group 1	AGG	<u>58.59</u>	54.89	41.66
	INDV	56.30	<u>55.32</u>	<u>53.52</u>
	FED	<b>60.03</b>	<b>65.57</b>	<b>55.61</b>
Group 2	AGG	57.40	51.25	33.05
	INDV	<u>58.14</u>	<u>55.61</u>	<u>53.03</u>
	FED	<b>61.67</b>	<b>66.62</b>	<b>57.48</b>

Hypothesis: Federated learning creates an ensemble model

# Comparison of Different Humor Recognition Models

- Without pretrained language model
  - DV-LR: Document vectors + Logistic Regression
  - WV-RF: word2vector + Random Forest Classifier
  - WV-CNN-HN: word2vector + CNN + Highway + fully connected classifier
- With pretrained language model
  - BERT-FZ/FT: BERT base version with pretrained weights *Freezed* or *FineTuned*
  - BERT-L/C/M: BERT Large or Cased or Multilingual Versions.
  - ALBERT: Faster BERT
- With pretrained language model and federated training strategy
  - FedHumor: BERT base + Federated Training

Table 3: Test performance (macro-averaged)

	Precision	Recall	$F_1$ score
DV-LR	53.69	53.67	53.64
WV-RF	56.70	56.10	55.20
WV-CNN-HN	56.20	54.70	51.90
BERT-FZ	54.15	53.71	52.53
BERT-FT	<u>64.91</u>	<u>64.88</u>	<u>64.87</u>
BERT-L	64.48	64.48	64.47
BERT-C	62.69	62.65	62.62
BERT-M	62.11	62.08	62.06
ALBERT	61.06	61.05	61.04
FedHumor	<b>66.60</b>	<b>66.56</b>	<b>66.53</b>

# Thank You



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# Experiment – Dataset

- We use the SemEval-2020 shared Task 7 - assessing the funniness of edited news headlines – for experiments.
- The original dataset contains the average ratings from 5 human annotators using a value in the range [0, 1, 2, 3].

Table 1: Statistics of the public dataset

	Train	Validation	Test
Number of samples	9,652	2,419	3,024
Average Rating	0.936	0.935	0.940
Minimum Rating	0.000	0.000	0.000
Maximum Rating	3.000	3.000	2.800

# Synthetic Data Generation

- Sort the jokes by their original average ratings.
- A user has only one humor preference  $\alpha_i$ .
- $\alpha_i$  is defined as a **transition point** in the funniness interval.

