A Flexible Framework for Communication-Efficient Machine Learning

AAAI'21

Presented by,

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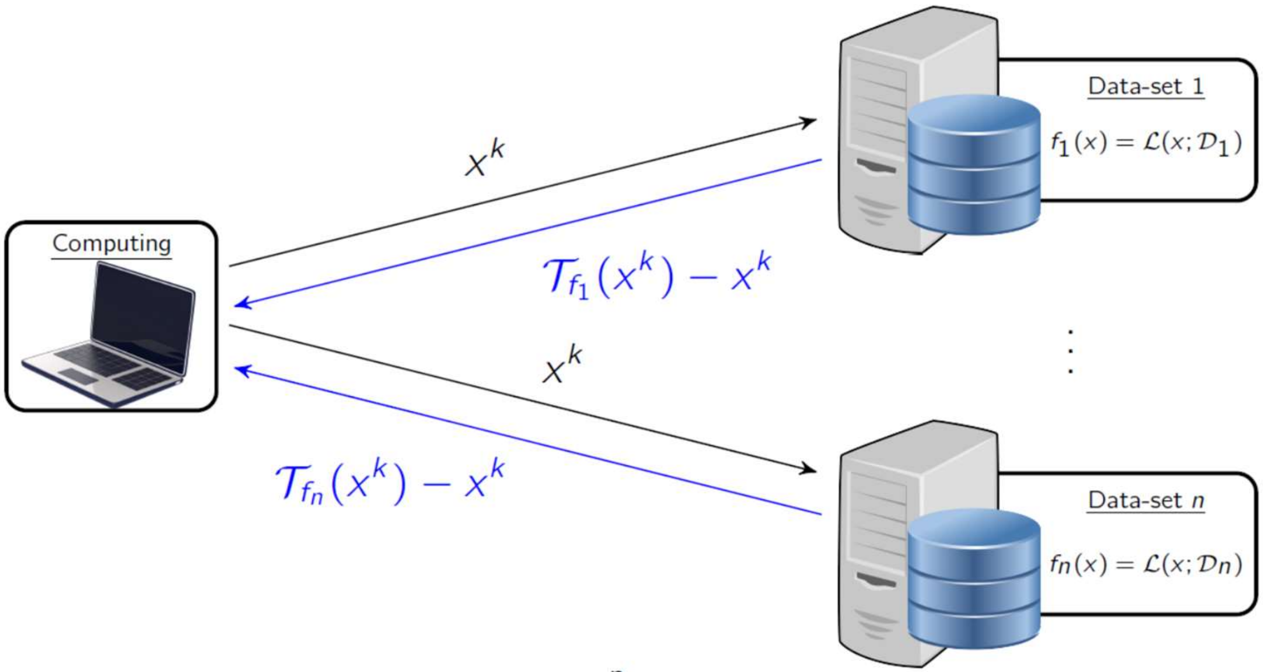
Outline

- Motivation
- Compression: methods and justification
- Theoretical results
- Numerical experiments and discussion
- Conclusion

Distributed Machine Learning



$$x^{k+1} = x^k + \sum_{i=1}^{n} [\mathcal{T}_{f_i}(x^k) - x^k].$$

- State-of-the-art problems have large dimension d (millions of parameters).
- 64 × d communicated bits per iteration per node.
- Performance bottleneck has shifted from computation to communication!
    - Neural network training: communication dominates 80% of run time

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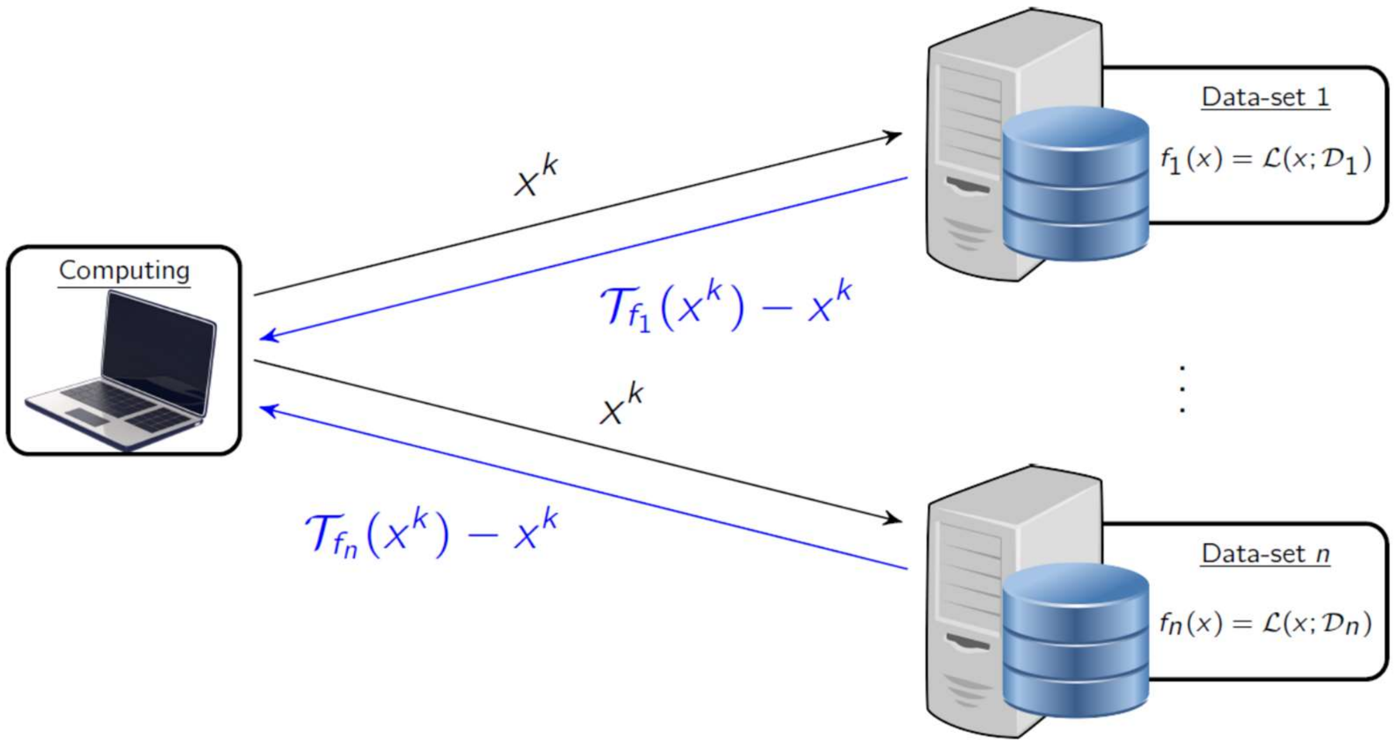
Strategies to Reduce Communication Bottleneck



- Asynchronous computation
- Client sampling
- Communication period to update global parameters
- **Compression**

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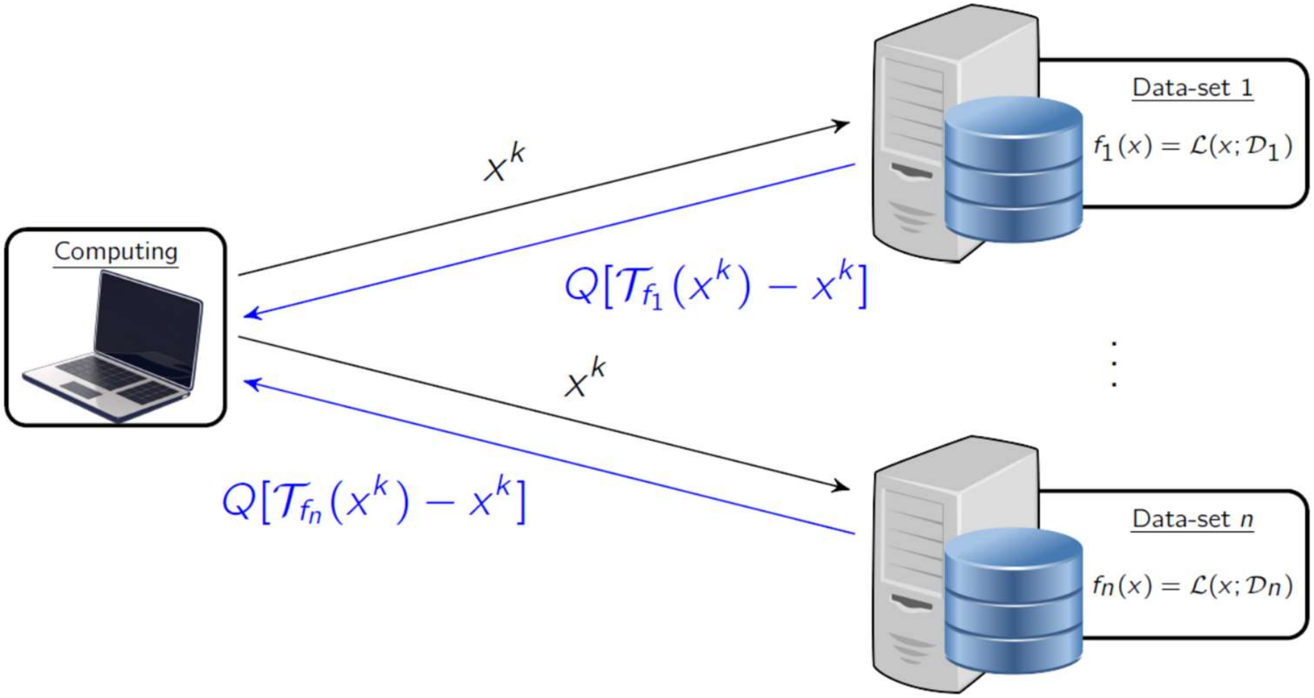
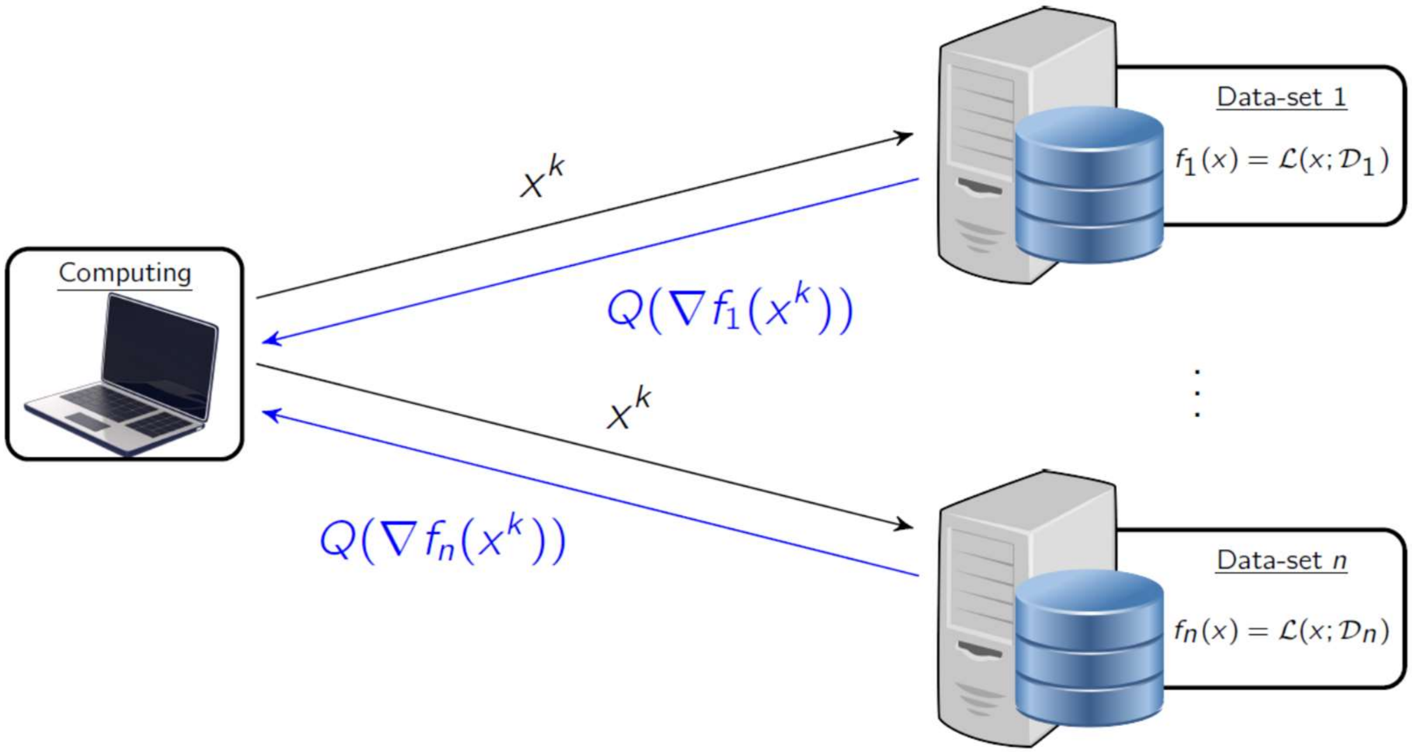
Compression Methods for Reducing Communications



$$x^{k+1} = x^k + \sum_{i=1}^{n} Q\left(\mathcal{T}_{f_i}(x^k) - x^k\right).$$

- Compression Q(·) can be
  - Sparsification: send only most important gradient elements.
  - Quantization: reduce precision on elements (e.g., sign compression).

Gradient Compression Methods



$$x^{k+1} = x^k - \gamma \sum_{i=1}^{n} Q(\nabla f_i(x^k)).$$

- Gradient compression in distributed learning

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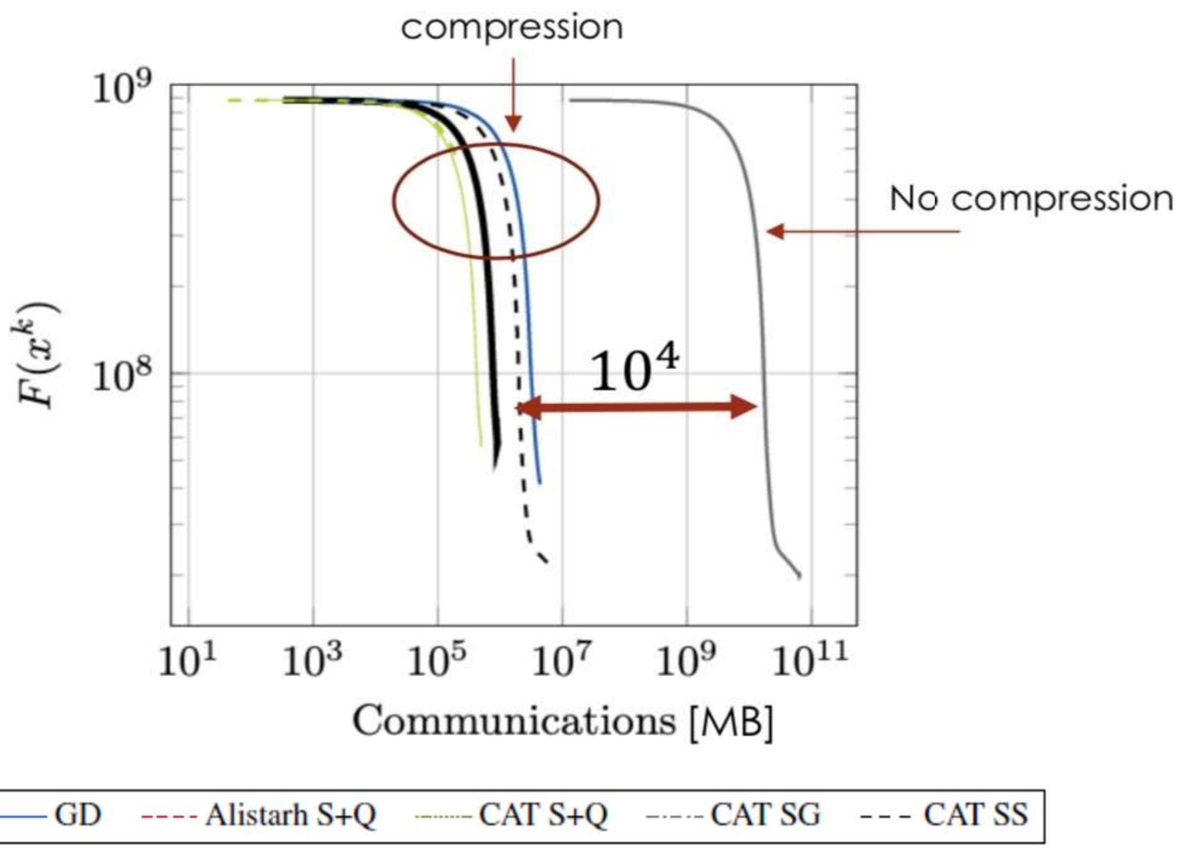
Gradient compression works well in practice



- Distributed data: server (Ericsson Kista) 500 km away from the data (Lund).
- ×1000 communication saving, compared to full-precision algorithms.

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Lack of theoretical justification for gradient compression

Communication Complexity (Tsitsiklis & Luo, 1987)

$$\texttt{strongly convex:} \quad \underset{x \in \mathbb{R}^d}{\text{minimize}} \quad \sum_{i=1}^{n} f_i(x)$$

For every algorithm there exists $f_i(\cdot)$ such that

$$d \times \log\left(\frac{1}{\epsilon}\right) \text{ bits}$$

are need to be communicated to find an ϵ-solution.

- Communication complexity grows at least linearly with d .
- **In the worst case, compression does not improve efficiency!**

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Challenges

- Communication benefits are often realized after a careful tuning of the compression level before training
- Most existing compression schemes are agnostic of the disparate communication costs for different technologies
- No universally good compressor that works well on all problems (worst-case communication complexity of any optimization methods)
- Worst-case bounds do not explain communication efficiency improvements.
- Communication efficiency achieved by hyperparameter optimization.

Contributions

- Explain efficiency by data/problem dependent complexity bounds.
- Design adaptive compression algorithms that
  - maximize communication efficiency automatically
  - adjust to data on-line and communication technology used i.e.,
- Find a good balance between the communication savings and suboptimality guarantees of the solution
  - Focus on adaptive compression,
  - Strikes this balance by adjusting the compression level online, e.g.
  - by optimizing the transmitted bits per iteration.

Initial Setting: Sparsified Gradient Descent

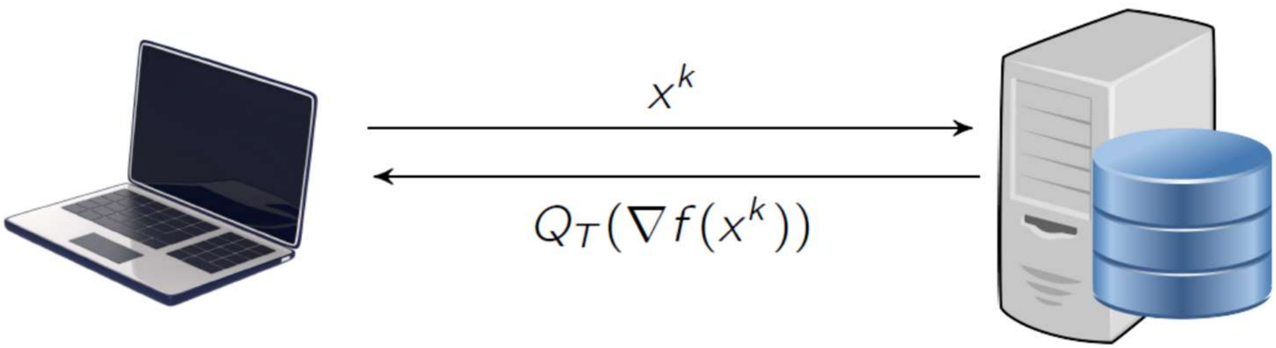
- Consider sparsified gradient descent

$$x^{k+1} = x^k - \gamma Q_T(\nabla f(x^k)),$$

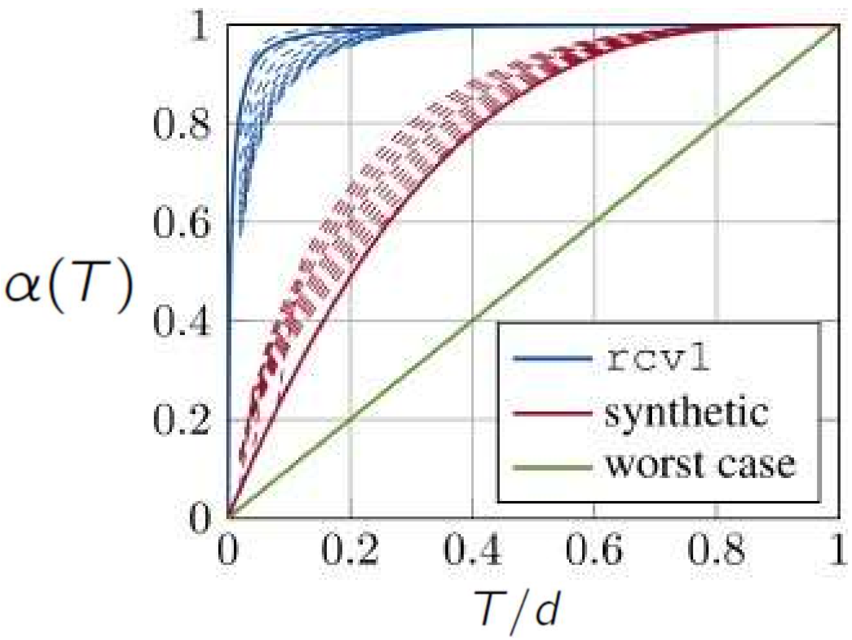
- where $Q_T(\cdot)$ with sparsity budget T is defined by

$$[Q_T(g)]_i = \begin{cases} g_i & \text{if} \quad i \in I_T(g) \\ 0 & \text{otherwise} \end{cases}$$

- where $I_T(g)$ has T indices of components with the largest absolute magnitude.



Why does sparsification improve communication efficiency?



Proportional Gradient Energy

$$\alpha(T) = \frac{||Q_T(\nabla f(x))||^2}{||\nabla f(x)||^2}$$

- **Worst Case**: Gradient energy is distributed evenly among all components.
  - $\alpha(T) = T/d$.
- **Real (sparse) Data**: Gradient energy is concentrated on few components.
  - $\alpha(T) \geq T/d$.

Sparsified Gradient Descent: Descent Lemma

Lemma (Generalized Descent Lemma)

Consider the minimization over $F(x)$ which is L-smooth and let $\gamma = 1/L$. Then for any $x, x^+ \in \mathbb{R}^d$ with

$$x^+ = x - \gamma Q_T(\nabla F(x))$$

we have

$$F(x^+) \leq F(x) - \frac{\alpha(T)}{2L}||\nabla F(x)||^2.$$

$$\alpha(T) \;=\; ||Q_T(\nabla F(x))||^2/||\nabla F(x)||^2$$

- *α(T)* implies the progress sparsification methods can make in each iteration.
- Classical gradient descent lemma when *α(T)* = 1.
- *α(T) ≥ T /d* (with equality for the worst-case energy distribution).

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Sparsified Gradient Descent: Data-dependent Complexity

- From the descent lemma, the data-dependent iteration complexities are derived

Iteration Complexity

Upper Bound	μ-convex	convex	nonconvex
No-Compression	A_ϵ^{SC}	A_ϵ^{C}	A_ϵ^{NC}
Data-Dependent	$\frac{1}{\bar{\alpha}_{\mathrm{Data}}} A_\epsilon^{\mathrm{SC}}$	$\frac{1}{\bar{\alpha}_{\mathrm{Data}}} A_\epsilon^{\mathrm{C}}$	$\frac{1}{\bar{\alpha}_{\mathrm{Data}}} A_\epsilon^{\mathrm{NC}}$
Worst-Case	$\frac{d}{T} A_\epsilon^{\mathrm{SC}}$	$\frac{d}{T} A_\epsilon^{\mathrm{C}}$	$\frac{d}{T} A_\epsilon^{\mathrm{NC}}$

where α(T) ≥ α¯Data.

Communicated bits to reach ϵ-accuracy (single precision)

- No compression: $32 A_\epsilon \times d$
- Worst case : $32 A_\epsilon \times d$
- Data-dependent : $32 A_\epsilon \times \frac{T}{\bar{\alpha}_{\mathrm{Data}}}$

$$\mathrm{SpeedUp}(T) = \frac{d}{T} \Big/ \frac{1}{\bar{\alpha}_T} = \frac{\bar{\alpha}_T}{T/d}$$

$$A_\epsilon^{\mathrm{SC}} = \kappa \log\left(\frac{F(x^0)-F^\star}{\epsilon}\right), \quad A_\epsilon^{\mathrm{C}} = \frac{2L\|x^0-x^\star\|^2}{\epsilon}, \quad A_\epsilon^{\mathrm{NC}} = \frac{2L(F(x^0)-F^\star)}{\epsilon}.$$

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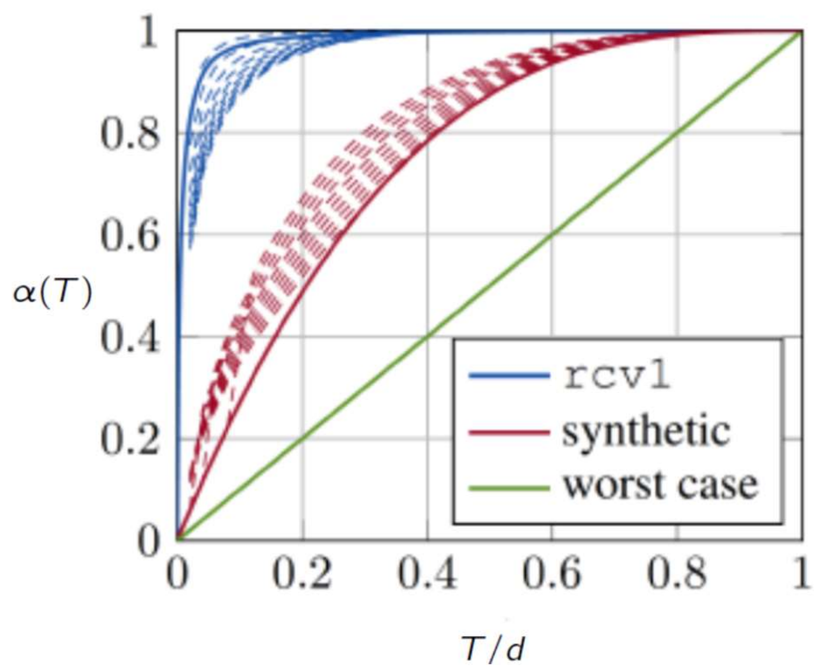
Why does sparsification improve communication efficiency?



For RCV1 (and many real data-sets)

$$\frac{1}{\bar{\alpha}_{\mathrm{Data}}} << \frac{d}{T}$$

Data dependent bound: 1000 fold communication improvement!!

Adaptive gradient compression

- **Main Idea**: Find sparsity budget *T* that maximizes descent per iteration, i.e.

$$T = \underset{T=1,2,\ldots,d}{\operatorname{argmax}} \ \text{Efficiency}(T) := \underset{T=1,2,\ldots,d}{\operatorname{argmax}} \frac{\alpha(T)}{\text{Cost}(T)}$$

- *α(T)/Cost(T)* attains its minimum over T = 1, 2, . . . , d.
- *α(T)* and *Cost(T)* easily measured online.
  - *α(T)* adapted to compression used.
  - *Cost(T)* adapted to technology or application.

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Communication Cost: Bits, Packets, Energy and Beyond

- *Cost(T)* →

communication overhead

$$\boxed{C(T) = c_1 \times \lceil P(T)/P_{\max} \rceil + c_0}$$

cost of transmitting a single payload byte

number of payload bits per packet

payload

$$\boxed{\begin{aligned} P^{\mathrm{S}}(T) &= T \times (\lceil \log_2(d) \rceil + \mathrm{FPP}) \text{ bits} \\ P^{\mathrm{SQ}}(T) &= \mathrm{FPP} + T \times \lceil \log_2(d) \rceil \text{ bits,} \end{aligned}}$$

- For example, if we just count transmitted bits (**$c_1 = 1$**), then a single UDP packet transmitted over the Ethernet requires an overhead of,

  $c_0 = 54 \times 8$ bits and can have a payload of up to 1472 bytes.

Communication Adaptive Tuning (CAT) Algorithms

- At iteration $k = 0, 1, 2, \ldots$
- **Step 1** (Adaptive tuning):
  - tune T adaptively to optimize the communication efficiency
  - hyper-parameter optimization not required

$$\boxed{T^k = \operatorname*{argmax}_{T=1,2,\ldots,d} \frac{\alpha^k(T)}{\mathrm{Cost}(T)}}$$

- **Step 2** (Compressed gradient):

$$\boxed{x^{k+1} = x^k - \gamma Q_{T^k}(\nabla f(x^k))}$$

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Extensions of Communication Adaptive Tuning (CAT)

- Sparsification and Quantization (S+Q).

$$[Q_T(g)]_i = \begin{cases} \|g\|\mathtt{sign}(g_i) & \text{if } i \in I_i(g) \\ 0 & \text{otherwise.} \end{cases}$$

- Stochastic Sparsification (for stochastic, multi-node optimization).

$$[Q_T(g)]_i = \frac{g_i}{p_i}\xi,$$

- where

$$\xi \sim \mathtt{Bernoulli}(p_i)$$

$$\textstyle\sum_i p_i = T$$

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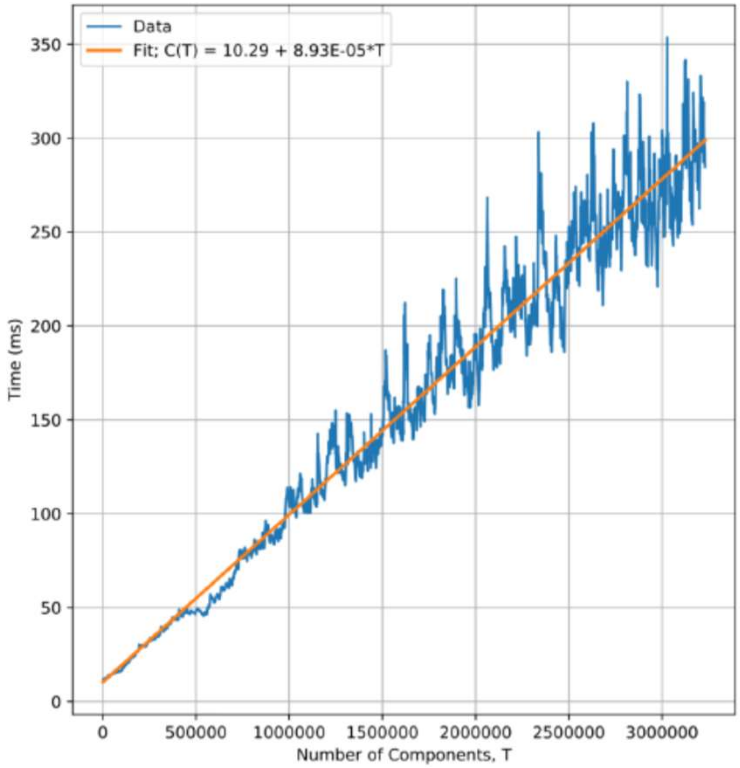
Communication Costs

- Many Possibilities:
  - Bits, energy, transmission time etc.
  - Build from protocols/standards
  - Build from empirical measurements

- Affine cost: Cost(T) = $c_0 + c_1 T$
  - c_0 packet header, c_1 cost per entree
  - Floats over Ethernet c_0 = 54, c1 = 4 + log2(d
  - Empirical Measurements (see figure)

- Packet cost: Ethernet $\mathtt{Cost}(T) = c_0 + c_1 \lceil \frac{P(T)}{P_{\max}} \rceil$
  - IEEE 802.15.4 (low energy wireless)

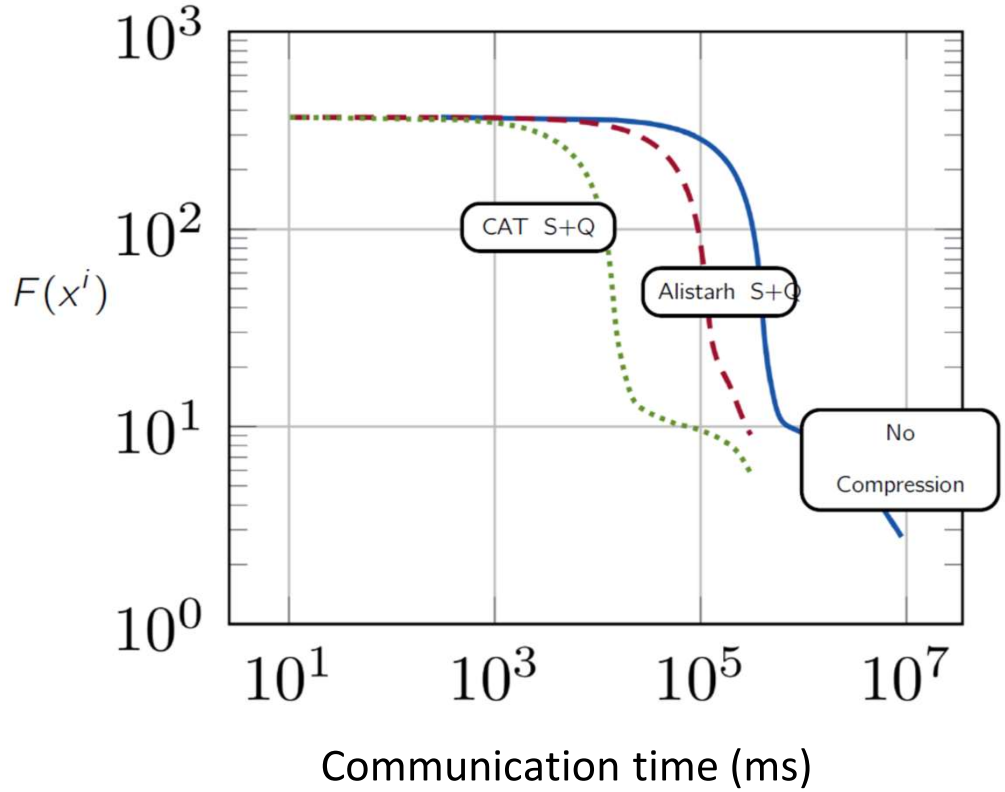


Communication times (s)

Experiment Settings

- CAT framework for dynamic sparsification and quantization (S+Q)
- Single node: single-master, single-worker setup
- URL data set with 2.4 million data points and 3.2 million features
- Distributed data: server (Ericsson Kista) 500 km away from the data (Lund)
- 1000 Mbit Internet connection using ZMQ library

Single-node Architecture

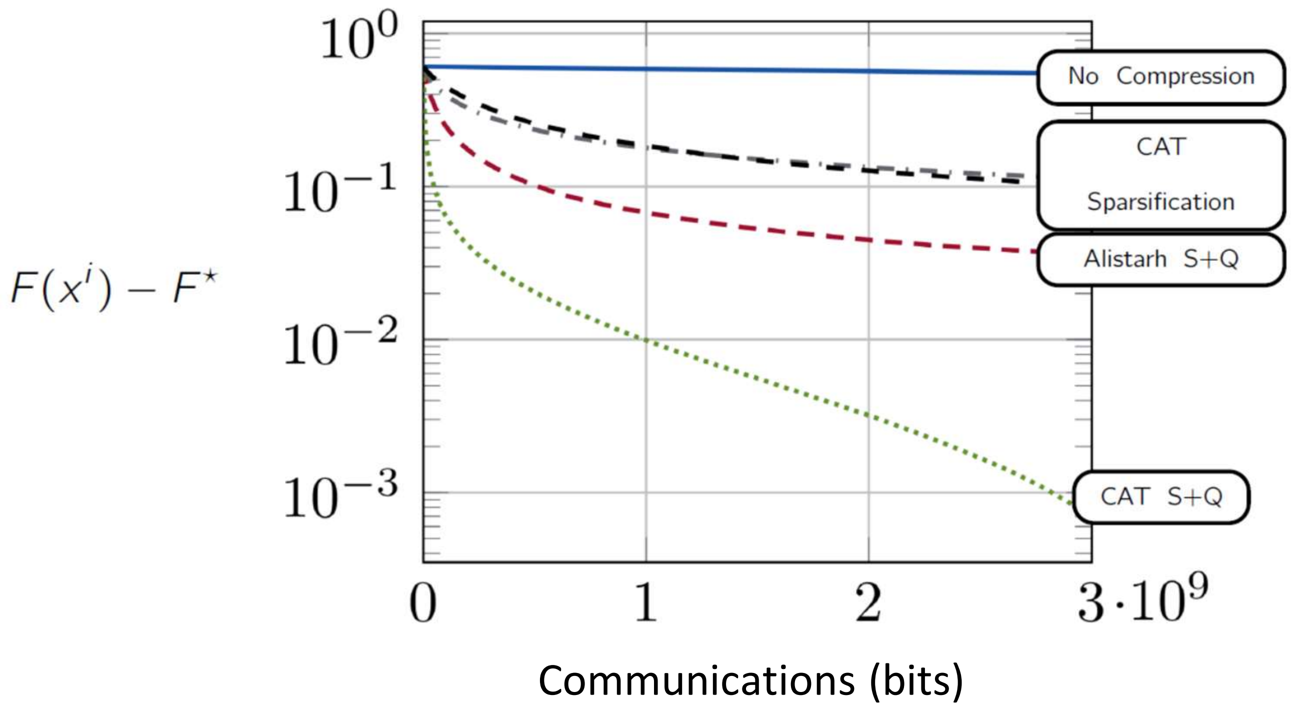


- CAT S+Q outperforms GD and Alistarh's S+Q up to two orders and one order of magnitude, respectively, in communication efficiency.

Experiment Settings – multi-node

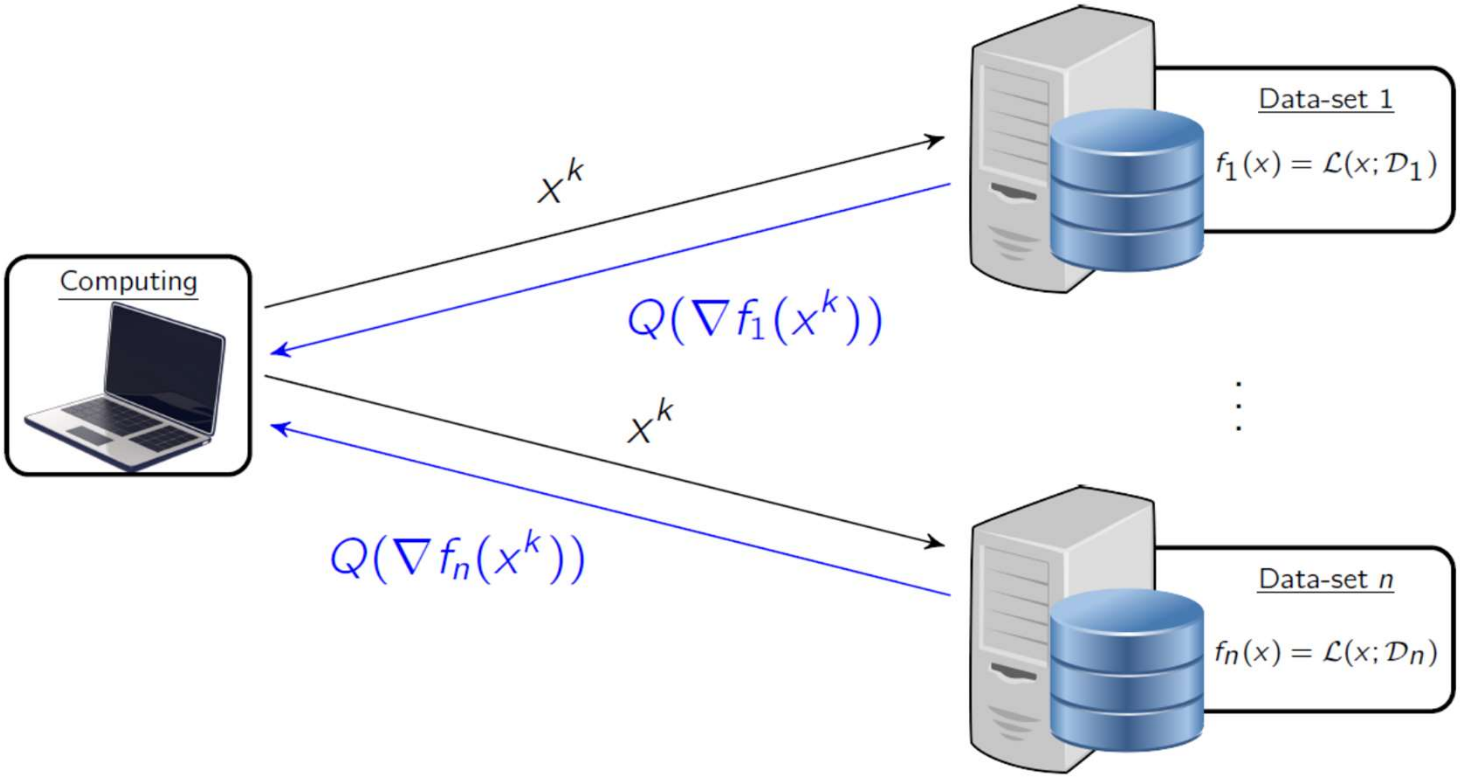
- CAT framework on
  - deterministic sparsification (SG)
  - stochastic sparsification (SS)
  - Sparsification with quantization (S+Q)
- RCV1 data set : 47,236 features, and 697,641 data points.
- Wireless communication scenario (e.g, IEEE 802.15.4) with 512 byte packets.
- Multi-node: 4 nodes using MPI, splitting the data evenly between the nodes.

Multiple-node Architecture



- CAT S+Q outperforms all other compression schemes
- CAT is roughly 6 times more communication efficient than (Alistarh et al. 2017) for the same compression scheme (compare number of bits needed to reach ϵ = 0.4).

Open Problems



- CAT for federated optimization
- CAT for error feedback, etc.

CAT Frameworks for Distributed Architectures

Lemma

Consider the minimization over $F(x) = \sum_{i=1}^{n} F_i(x)/n$, where each function $F_i(x)$ is μ-strongly convex and L-smooth. Let the sequence $\{x_k\}$ be generated by

$$x^{k+1} = x^k - \frac{\gamma^k}{n} \sum_{i=1}^{n} Q_T(\nabla F_i(x^k)),$$

where $\mathbf{E}[Q_T(v)] = v$ and $\omega(T) = \|v\|^2/\mathbf{E}\|Q_T(v)\|^2$, and let $\gamma^k = \alpha/(k+1)$ for $\alpha > 0$. Then, the communication complexity to reach $\mathbf{E}[F(x^k) - F^\star] \leq \epsilon$ is

$$\frac{\mathtt{Cost}(T)}{\omega_{\max}(T)} \cdot \min\left(\frac{B_1}{\sqrt{\epsilon}}, \frac{B_2}{\epsilon}\right),$$

for $B_1, B_2 > 0$.

- Limitations:
  - CAT with the same compression level T for all clients.

CAT Frameworks for Distributed Stochastic Sparsification

Lemma

Consider the minimization over $F(x) = \sum_{i=1}^{n} F_i(x)/n$*, where each function* $F_i(x)$ *is* μ*-strongly convex and* L*-smooth. Let the sequence* $\{x_k\}$ *be generated by*

$$x^{k+1} = x^k - \frac{\gamma}{n} \sum_{i=1}^{n} Q_T(\nabla F_i(x^k))$$

where $\mathbf{E}[Q_T(v)] = v$ *and* $\omega(T) = \|v\|^2 / \mathbf{E}\|Q_T(v)\|^2$*, and let* $\gamma_k = \alpha/(k+1)$ *for* $\alpha > 0$*. Then, the communication complexity is*

$$\frac{\mathtt{Cost}(T)}{\omega_{\max}(T)} \cdot \min\left(\frac{B_1}{\sqrt{\epsilon}}, \frac{B_2}{\epsilon}\right).$$

for $B_1, B_2 > 0$.

- **Questions**:

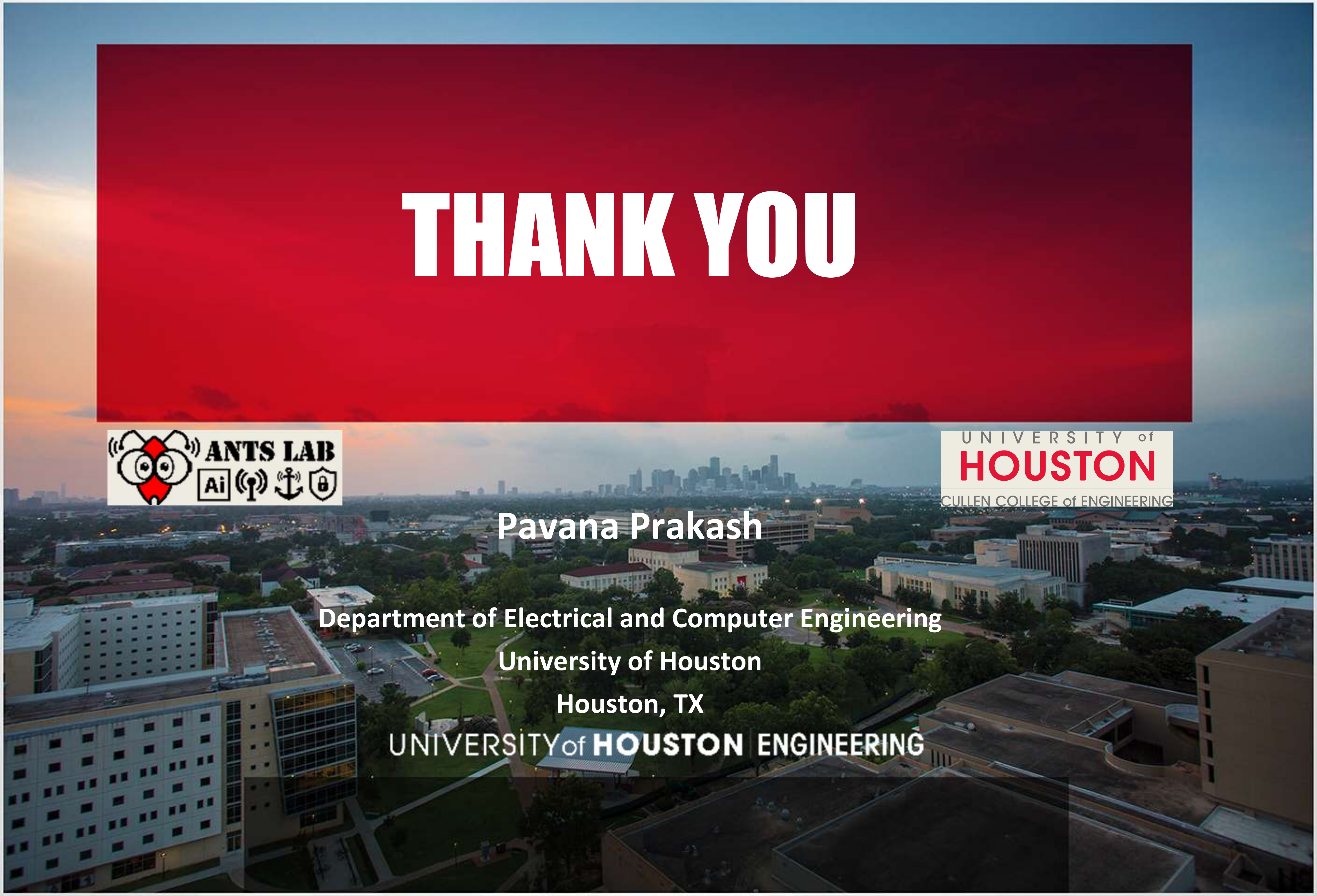
1. How to tune local compression level without synchronization?
2. How to tune deterministic compression for federated architectures?

Conclusions

- **Existing Works:**
- Worst-case bound does not explain communication efficiency by compression.
- Compressions not adapted to technology or relevant communication costs.

- **Contributions**:
- Explain improved efficiency by data/problem dependent complexity.
- Design adaptive compression that
  - optimizes overall communication efficiency automatically.
  - adjusts to data online and to any communication technology/application used.
  - leads to significant communication savings, compared to existing compression.

- **Open Problems**: CAT frameworks for distributed and federated optimization



THANK YOU

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