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(54) TECHNIQUES FOR COMPRESSING A MACHINE-LEARNING MODEL

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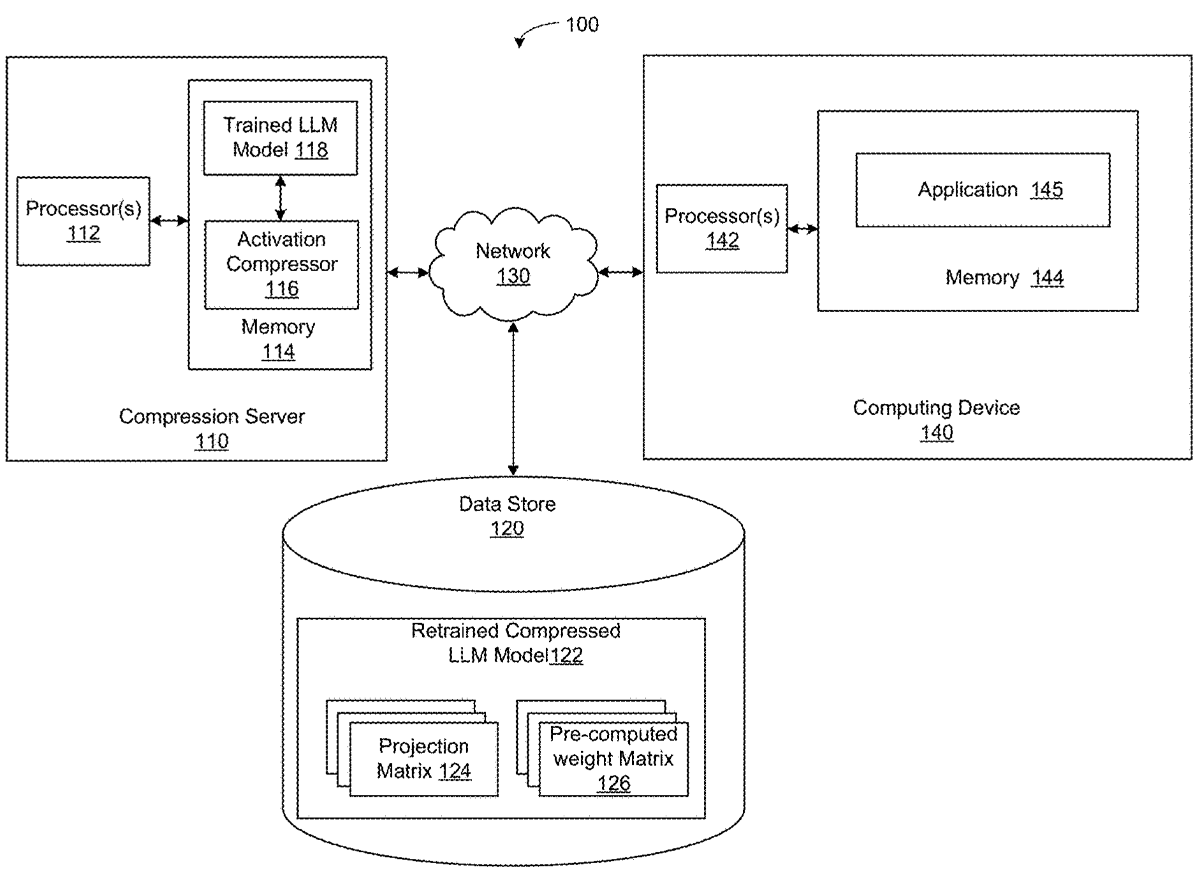
CPC *G06N 3/0495* (2023.01)

(57) **ABSTRACT**

Techniques for compressing a machine learning mode include executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model; for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model; identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models; generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix; and generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.



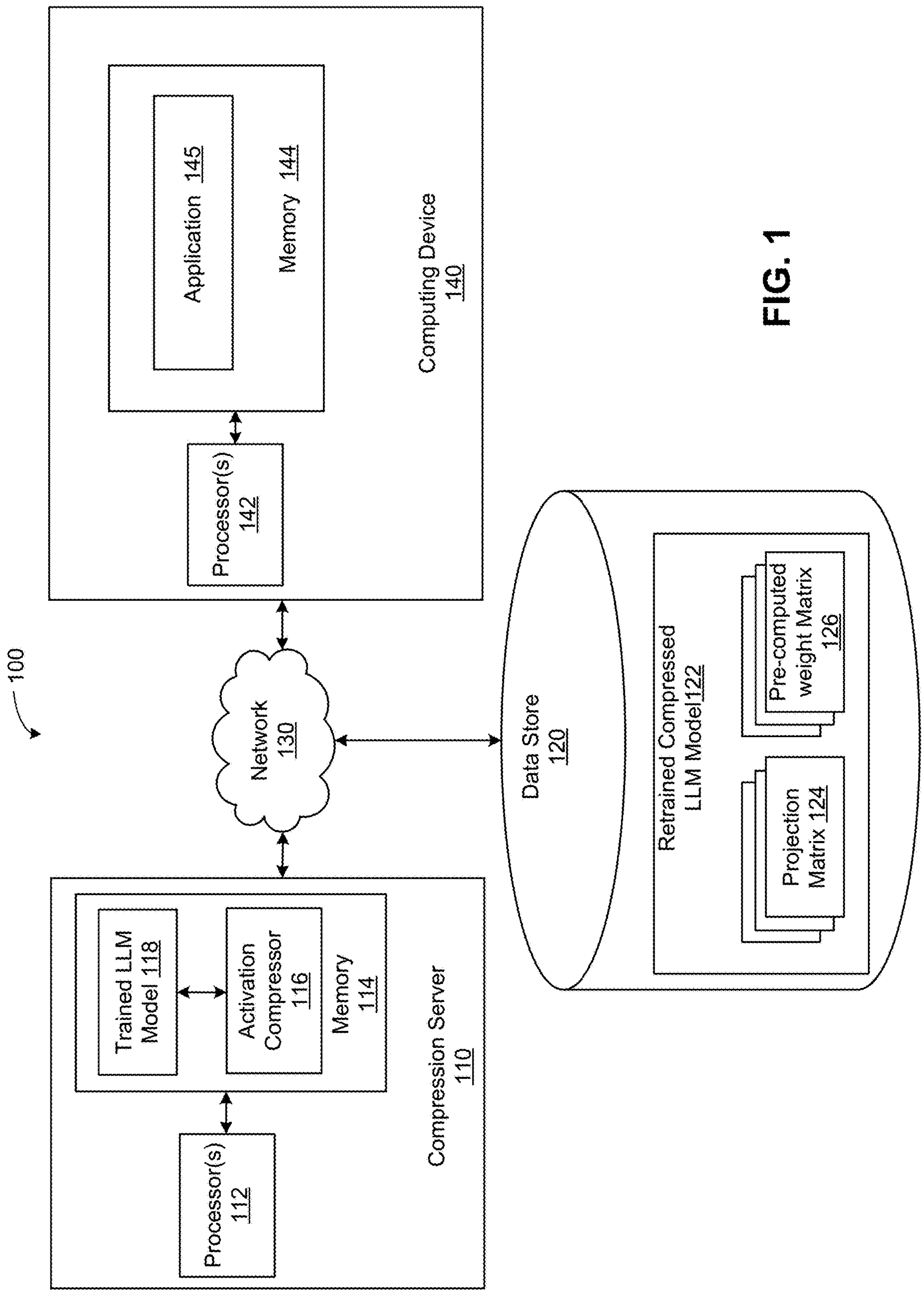

100
Application 145
Memory 144
Processor(s) 142
Computing Device 140
Network 130
Data Store 120
Retrained Compressed LLM Model122
Pre-computed weight Matrix 126
Projection Matrix 124
Trained LLM Model 118
Activation Compressor 116
Memory 114
Processor(s) 112
Compression Server 110

FIG. 1

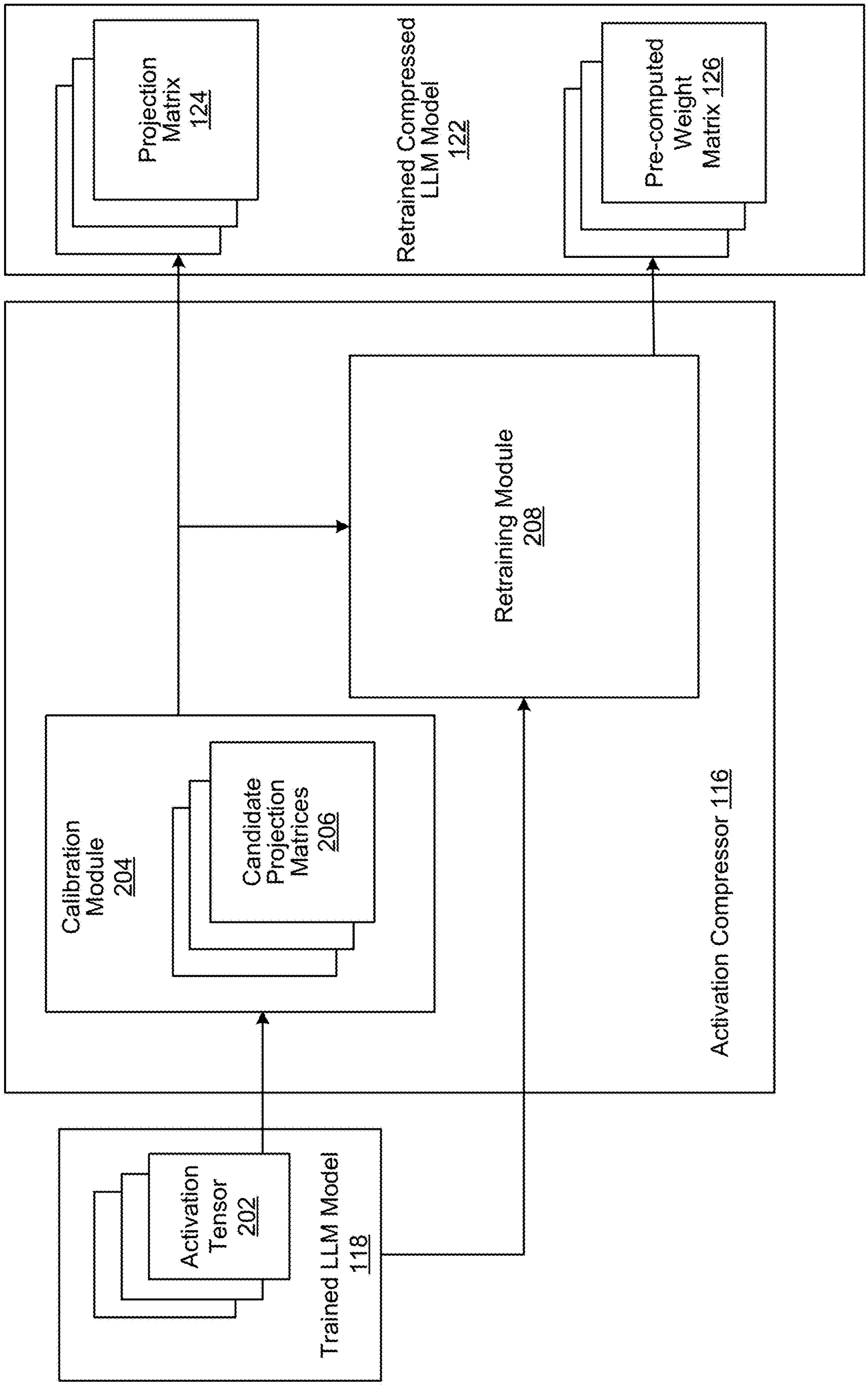

Retrained Compressed LLM Model 122
Projection Matrix 124
Pre-computed Weight Matrix 126
Activation Compressor 116
Calibration Module 204
Candidate Projection Matrices 206
Retraining Module 208
Trained LLM Model 118
Activation Tensor 202

FIG. 2

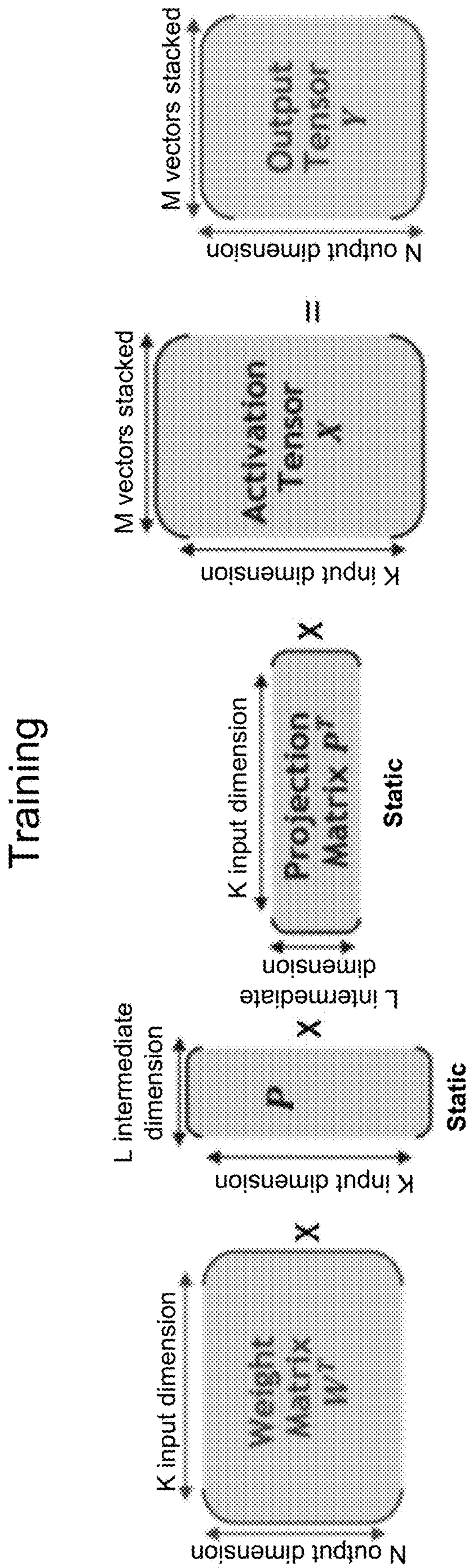

Training
N output dimension
K input dimension
Weight Matrix W^T
x
K input dimension
L intermediate dimension
P
Static
x
L intermediate dimension
K input dimension
Projection Matrix P^T
Static
x
K input dimension
M vectors stacked
Activation Tensor X
=
N output dimension
M vectors stacked
Output Tensor Y

FIG. 3

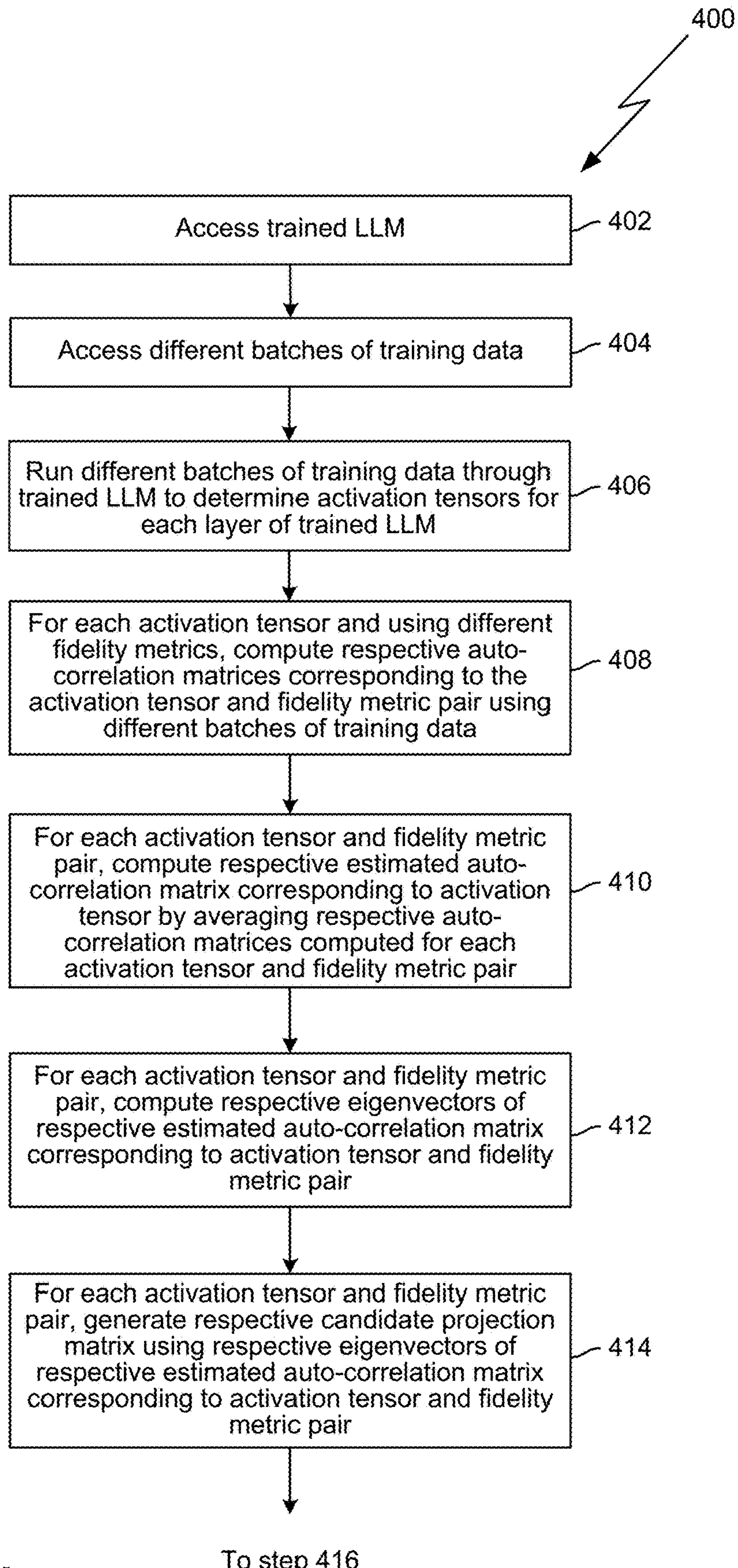

400
Access trained LLM
402
Access different batches of training data
404
Run different batches of training data through trained LLM to determine activation tensors for each layer of trained LLM
406
For each activation tensor and using different fidelity metrics, compute respective auto-correlation matrices corresponding to the activation tensor and fidelity metric pair using different batches of training data
408
For each activation tensor and fidelity metric pair, compute respective estimated auto-correlation matrix corresponding to activation tensor by averaging respective auto-correlation matrices computed for each activation tensor and fidelity metric pair
410
For each activation tensor and fidelity metric pair, compute respective eigenvectors of respective estimated auto-correlation matrix corresponding to activation tensor and fidelity metric pair
412
For each activation tensor and fidelity metric pair, generate respective candidate projection matrix using respective eigenvectors of respective estimated auto-correlation matrix corresponding to activation tensor and fidelity metric pair
414
To step 416

FIG. 4A

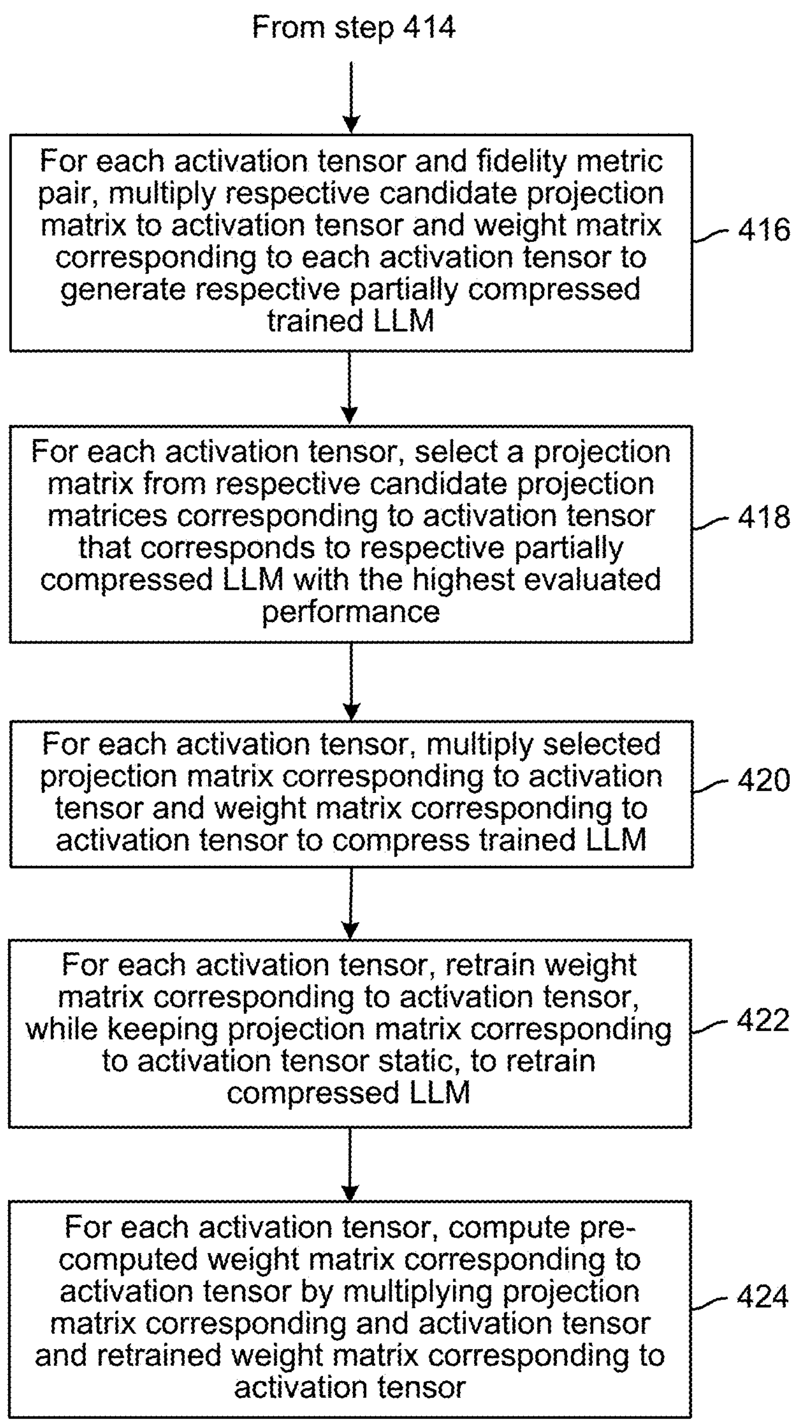

From step 414
For each activation tensor and fidelity metric pair, multiply respective candidate projection matrix to activation tensor and weight matrix corresponding to each activation tensor to generate respective partially compressed trained LLM
416
For each activation tensor, select a projection matrix from respective candidate projection matrices corresponding to activation tensor that corresponds to respective partially compressed LLM with the highest evaluated performance
418
For each activation tensor, multiply selected projection matrix corresponding to activation tensor and weight matrix corresponding to activation tensor to compress trained LLM
420
For each activation tensor, retrain weight matrix corresponding to activation tensor, while keeping projection matrix corresponding to activation tensor static, to retrain compressed LLM
422
For each activation tensor, compute pre-computed weight matrix corresponding to activation tensor by multiplying projection matrix corresponding and activation tensor and retrained weight matrix corresponding to activation tensor
424

FIG. 4B

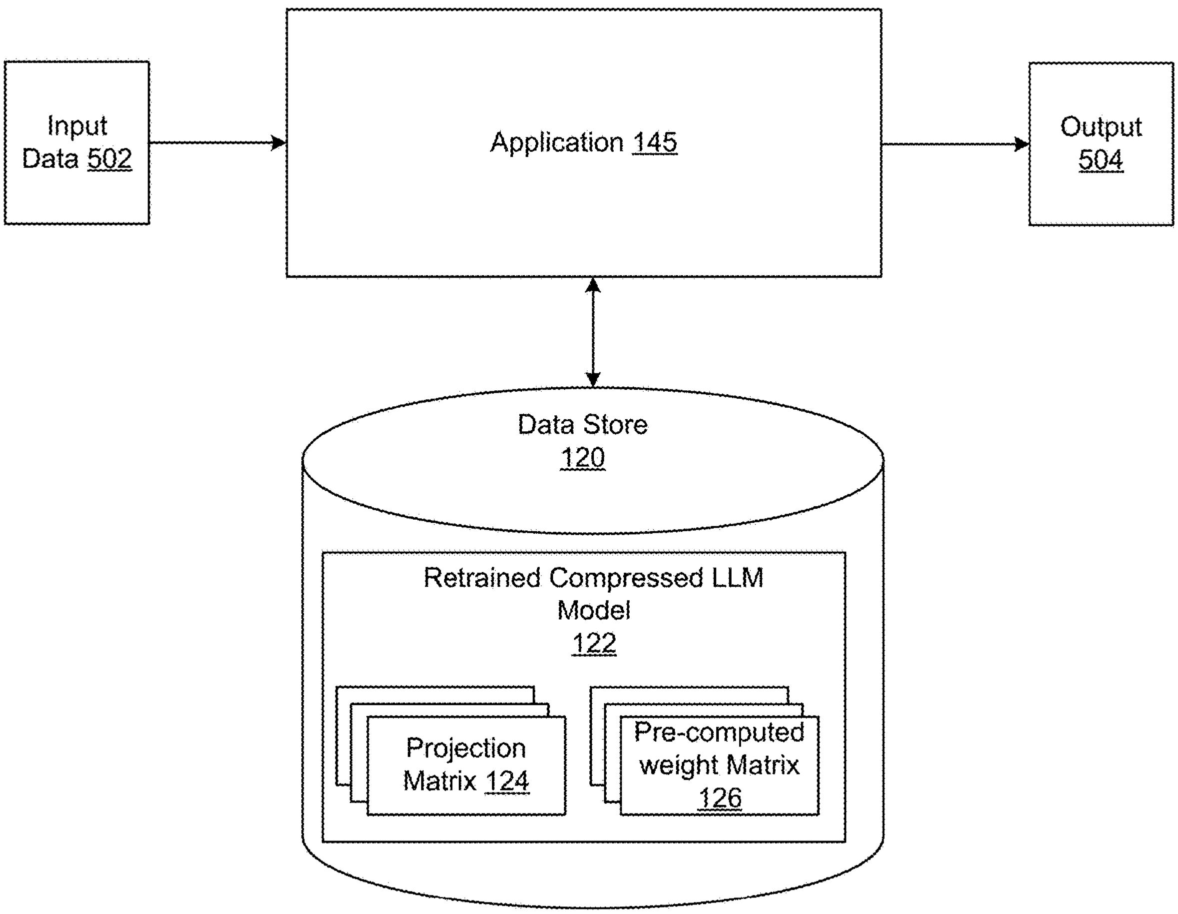

Input
Data 502
Application 145
Output
504
Data Store
120
Retrained Compressed LLM
Model
122
Projection
Matrix 124
Pre-computed
weight Matrix
126

FIG. 5

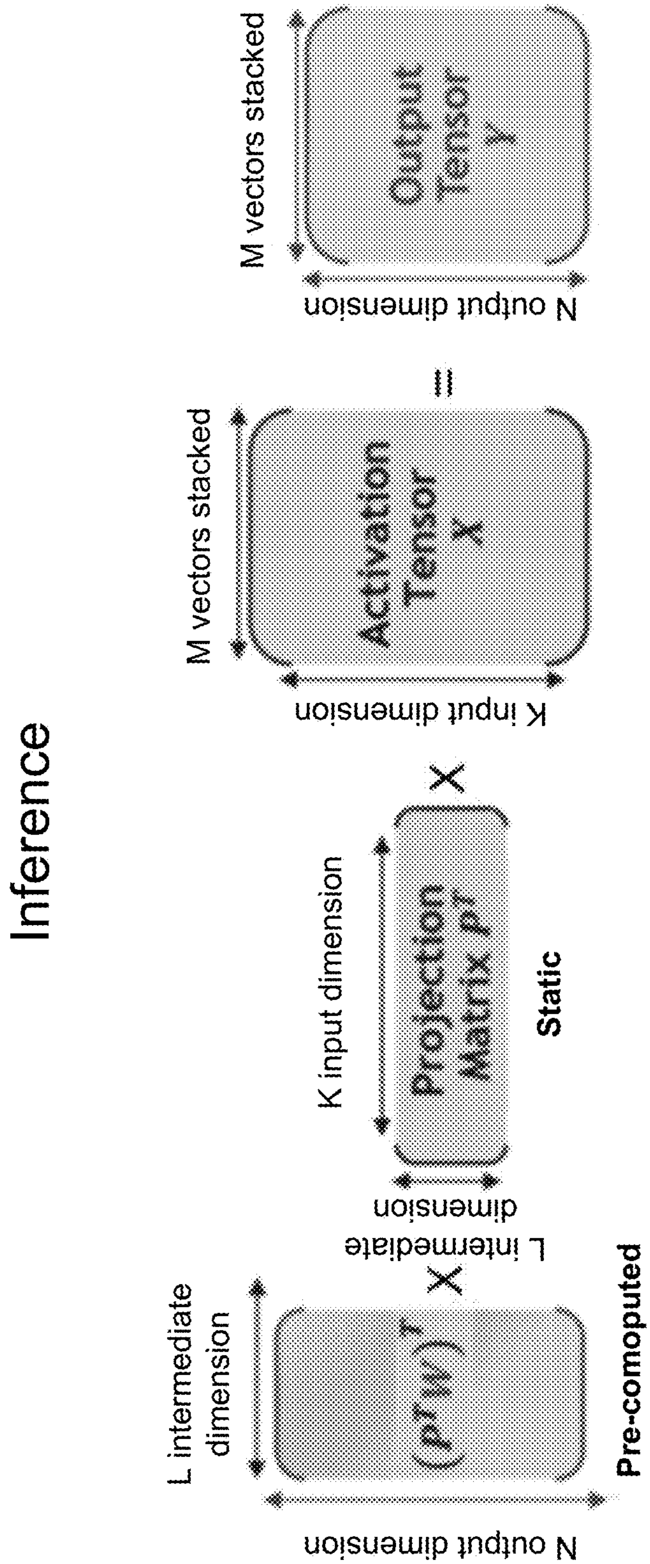
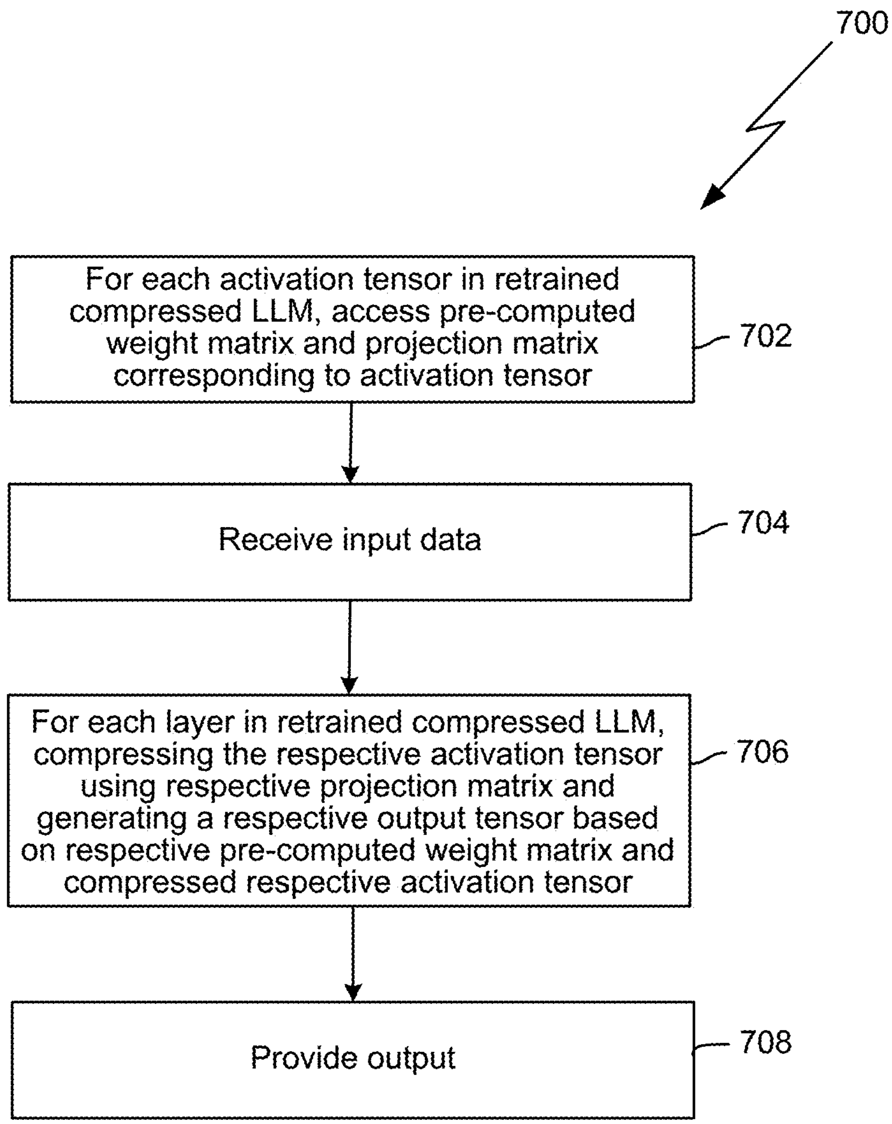

Inference
L intermediate dimension
N output dimension
$(P^T W)^T$
Pre-comoputed
×
L intermediate dimension
K input dimension
Projection Matrix P^T
Static
×
M vectors stacked
K input dimension
Activation Tensor X
=
M vectors stacked
N output dimension
Output Tensor Y

FIG. 6



700
For each activation tensor in retrained compressed LLM, access pre-computed weight matrix and projection matrix corresponding to activation tensor
702
Receive input data
704
For each layer in retrained compressed LLM, compressing the respective activation tensor using respective projection matrix and generating a respective output tensor based on respective pre-computed weight matrix and compressed respective activation tensor
706
Provide output
708

FIG. 7

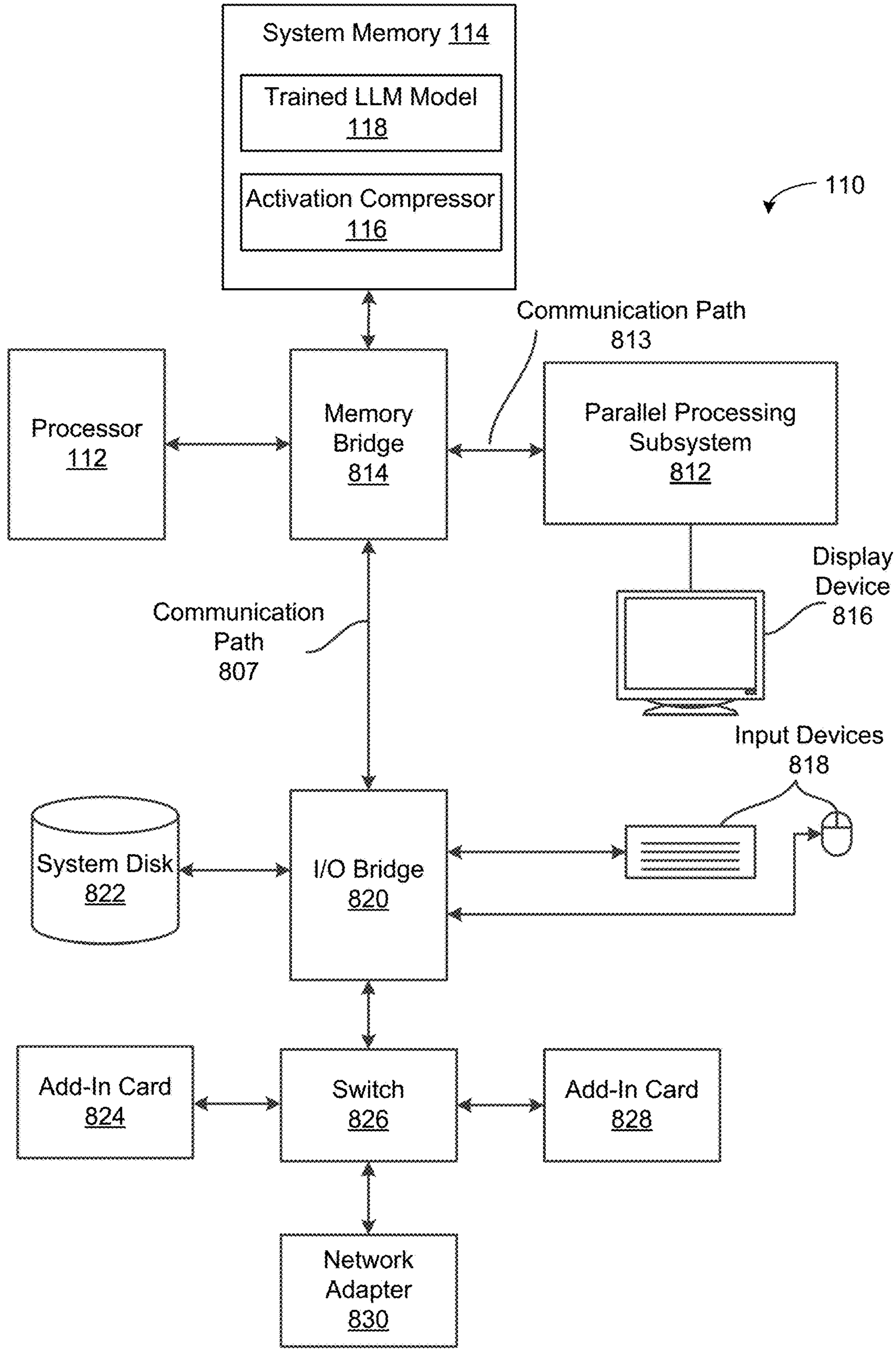

System Memory 114
Trained LLM Model 118
Activation Compressor 116
110
Communication Path 813
Processor 112
Memory Bridge 814
Parallel Processing Subsystem 812
Display Device 816
Communication Path 807
Input Devices 818
System Disk 822
I/O Bridge 820
Add-In Card 824
Switch 826
Add-In Card 828
Network Adapter 830

FIG. 8

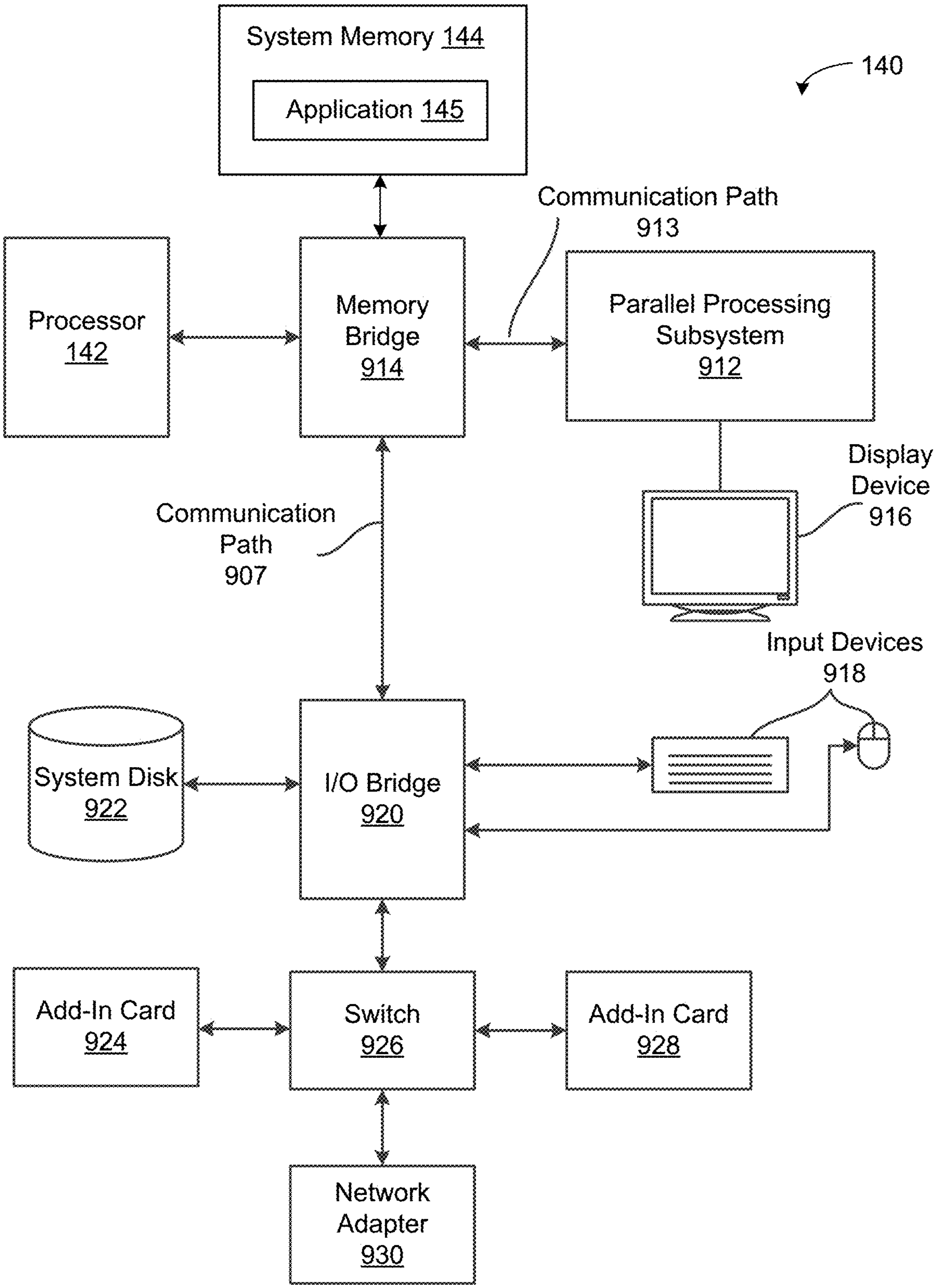

System Memory 144
Application 145
140
Communication Path
913
Processor
142
Memory
Bridge
914
Parallel Processing
Subsystem
912
Display
Device
916
Communication
Path
907
Input Devices
918
System Disk
922
I/O Bridge
920
Add-In Card
924
Switch
926
Add-In Card
928
Network
Adapter
930

FIG. 9

TECHNIQUES FOR COMPRESSING A MACHINE-LEARNING MODEL

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims benefit of the United States Provisional Patent Application titled "TECHNIQUES FOR EIGEN STATIC PRINCIPAL ACTIVATION COMPONENT ESTIMATION," filed Feb. 20, 2024, and having Ser. No. 63/555,815. The subject matter of this related application is hereby incorporated herein by reference.

BACKGROUND

Field of the Various Embodiments

[0002] The various embodiments relate generally to computer science and artificial intelligence and, more specifically, to techniques for compressing a machine-learning model.

Description of the Related Art

[0003] Machine learning can be used to discover trends, patterns, relationships, and/or other attributes related to large sets of complex, interconnected, and/or multidimensional data. To glean insights from large data sets, regression models, artificial neural networks, support vector machines, decision trees, naïve Bayes classifiers, and/or other types of machine learning models can be trained using input-output pairs in the data. In turn, the discovered information can be used to guide decisions and/or perform actions related to the data and/or other similar data.

[0004] Machine learning models can be very large and require specialized resources to train and execute once trained. For example, some trained large language models (LLMs) can include billions of parameters. Accordingly, various compression techniques, such as quantization and pruning, have been developed to reduce the number of parameters and computations needed for LLMs and other large machine learning models. Quantization is oftentimes used to reduce the precision of the parameter values included in a machine learning model, which reduces the overall size of the model as well as computational complexity when training the model and executing the trained model. For example, converting parameter value precision from a 32-bit representation to an 8-bit representation reduces the overall computational complexity of the trained model, which allows the trained LLM model to execute faster and also run on resource-constrained devices. Pruning is oftentimes used to reduce the number of parameters included in a LLM model by systematically removing portions of the LLM model, such as weights, neurons, or layers, during training. Removing portions of the LLM model increases the data sparsity associated with the LLM model parameters and reduces computational complexity when executing the trained LLM model. When data sparsity is implemented in a structured way, the removal process focuses on the order and location of the portions of the LLM model being eliminated. When data sparsity is implemented in an unstructured way, the removal process focuses on eliminating portions of the LLM model that have the lowest impact on accuracy.

[0005] One drawback of using quantization techniques for LLM model compression is that quantization results in model data and the computations using model data being represented using fewer bits. Reducing the number of bits used for model data and for related computations usually reduces model accuracy as well. Another drawback of using quantization techniques for LLM model compression is that specialized hardware is oftentimes needed to execute models, where the model is represented using a reduced number of bits. One drawback of using pruning techniques for LLM model compression is that structured pruning does not preserve accuracy of the model, because parts of the model with important information are removed. Another drawback of using pruning techniques for LLM model compression is that with unstructured pruning techniques, parts of LLM model are removed in an unpredictable order, causing pruned models to have sparse structures, leading to irregular patterns of computation and memory access. Accordingly, efficient execution of pruned models on hardware is challenging and difficult since standard hardware is not optimized for computations with sparse structures.

[0006] As the forgoing illustrates, what is needed in the art are more effective ways to compress LLM models.

SUMMARY

[0007] One embodiment of the present disclosure sets forth a computer implemented method for compressing machine learning models. The method includes executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model; for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model; identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models; generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix; and generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

[0008] Other embodiments of the present disclosure include, without limitation, one or more computer-readable media including instructions for performing one or more aspects of the disclosed techniques as well as one or more computing systems for performing one or more aspects of the disclosed techniques

[0009] At least one technical advantage of the disclosed techniques relative to the prior art is that the disclosed techniques perform compression on the activation tensors of a machine learning model. Activation tensors are known to exhibit many redundancies. Accordingly, the disclosed techniques provide better opportunities for dimensionality reduction. In addition, the compression operations enabled by the disclosed techniques can be executed on any processor and do not need specialized hardware. Further, the disclosed techniques do not need any optimizations at run time, thereby facilitating overall execution efficiency. In addition, the disclosed techniques reduce the computational cost of inferencing using a machine learning model. These technical advantages represent one or more technological improvements over prior art approaches.

BRIEF DESCRIPTION OF THE DRAWINGS

[0010] So that the manner in which the above recited features of the various embodiments can be understood in detail, a more particular description of the inventive concepts, briefly summarized above, may be had by reference to various embodiments, some of which are illustrated in the appended drawings. It is to be noted, however, that the appended drawings illustrate only typical embodiments of the inventive concepts and are therefore not to be considered limiting of scope in any way, and that there are other equally effective embodiments.

[0011] FIG. **1** illustrates a block diagram of a computer-based system configured to implement one or more aspects of the various embodiments;

[0012] FIG. **2** illustrates a block diagram of the activation compressor in FIG. **1**, according to various embodiments;

[0013] FIG. **3** illustrates computations of a compressed activation tensor, according to various embodiments;

[0014] FIGS. **4**A and **4**B are a flow diagram of method steps for compressing a trained LLM model, according to various embodiments;

[0015] FIG. **5** illustrates an application in more detail, according to various embodiments;

[0016] FIG. **6** illustrates computations of a compressed activation tensor during inferencing, according to various embodiments;

[0017] FIG. **7** is a flow diagram of method steps for compressing and executing retrained LLM model, according to various embodiments;

[0018] FIG. **8** is a more detailed illustration of compression server of FIG. **1**, according to the various embodiments; and

[0019] FIG. **9** is a more detailed illustration of computing device of FIG. **1**, according to the various embodiments.

DETAILED DESCRIPTION

[0020] In the following description, numerous specific details are set forth to provide a more thorough understanding of the various embodiments. However, it will be apparent to one skilled in the art that the inventive concepts may be practiced without one or more of these specific details.

System Overview

[0021] FIG. **1** illustrates a block diagram of a computer-based system **100** configured to implement one or more aspects of the various embodiments. As shown, system **100** includes, without limitation, a compression server **110**, a data store **120**, a network **130**, and a computing device **140**. Compression server **110** includes, without limitation, processor(s) **112** and a system memory **114**. Memory **114** includes, without limitation, an activation compressor **116** and a trained LLM model **118**. Computing device **140** includes, without limitation, processor(s) **142** and memory **144**. Memory **144** includes, without limitation, an application **145**. Data store **120** includes, without limitation, a retrained compressed LLM model **122**, including one or more projection matrices **124** and one or more pre-computed weight matrices **126**.

[0022] Compression server **110** shown herein is for illustrative purposes only, and variations and modifications are possible without departing from the scope of the present disclosure. For example, the number and types of processors **112**, the number and types of system memories **114**, and/or the number of applications included in the system memory **114** can be modified as desired. Further, the connection topology between the various units in FIG. **1** can be modified as desired. In some embodiments, any combination of the processor(s) **112** and the system memory **114** can be included in and/or replaced with any type of virtual computing system, distributed computing system, and/or cloud computing environment, such as a public, private, or a hybrid cloud system.

[0023] Processor(s) **112** receive user input from input devices, such as a keyboard or a mouse. Processor(s) **112** can be any technically feasible form of processing device configured to process data and execute program code. For example, any of processor(s) **112** could be a central processing unit (CPU), a graphics processing unit (GPU), an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), and so forth. In various embodiments any of the operations and/or functions described herein can be performed by processor(s) **112**, or any combination of these different processors, such as a CPU working in cooperation with a one or more GPUs. In various embodiments, the one or more GPU(s) perform parallel processing task, such as matrix multiplications and/or the like in LLM model computations. Processor(s) **112** can also receive user input from input devices, such as a keyboard or a mouse and generate output on one or more displays.

[0024] System memory **114** of compression server **110** stores content, such as software applications and data, for use by processor(s) **112**. System memory **114** can be any type of memory capable of storing data and software applications, such as a random-access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash ROM), or any suitable combination of the foregoing. In some embodiments, a storage (not shown) can supplement or replace system memory **114**. The storage can include any number and type of external memories that are accessible to processor(s) **112**. For example, and without limitation, the storage can include a Secure Digital Card, an external Flash memory, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, and/or any suitable combination of the foregoing.

[0025] Activation compressor **116** is configured to compress trained LLM model **118** by compressing the activation tensors of trained LLM model **118**. Activation compressor **116** compresses trained LLM model **118** by generating retrained compressed LLM model **122**, which includes projection matrices **124** and pre-computed weight matrices **126**. Activation compressor **116** then stores retrained compressed LLM model **122**, including projection matrices **124** and pre-computed weight matrices **126**, in data store **120**. The retrained compressed LLM model **122**, projection matrices **124**, and pre-computed weight matrices **126** can then be used in any suitable application, such as application **145** executing on computing device **140**. In some embodiments, activation compressor **116** compresses trained LLM model **118** or any number of trained LLM models. In some embodiments, during compression of trained LLM model **118** activation compressor **116** uses different fidelity metrics to determine projection matrices **124** that compress trained LLM model **118**. Trained LLM model **118** can be any type of technically feasible machine learning model. For example, in various embodiments, trained LLM model **118**

can be a transformer based LLM model, such as a generative pre-trained transformer (GPT), with any suitable architecture. The operations performed by activation compressor **116** to compress trained LLM model **118** are described in greater detail below in conjunction with FIGS. **2-4**.

[0026] Data store **120** provides non-volatile storage for applications and data in compression server **110** and computing device **140**. For example, and without limitation, training data, trained (or deployed) machine learning models and/or application data, including trained LLM model **118**, retrained compressed LLM model **122**, including projection matrices **124** and pre-computed weight matrices **126**, can be stored in the data store **120**. In some embodiments, data store **120** can include fixed or removable hard disk drives, flash memory devices, and CD-ROM (compact disc read-only-memory), DVD-ROM (digital versatile disc-ROM), Bluray, HD-DVD (high definition DVD), or other magnetic, optical, or solid state storage devices. Data store **120** can be a network attached storage (NAS) and/or a storage area-network (SAN). Although shown as coupled to compression server **110** and computing device **140** via network **130**, in various embodiments, compression server **110** or computing device **140** can include data store **120**.

[0027] Network **130** includes any technically feasible type of communications network that allows data to be exchanged between compression server **110**, computing device **140**, data store **120** and external entities or devices, such as a web server or another networked computing device. For example, network **130** can include a wide area network (WAN), a local area network (LAN), a cellular network, a wireless (WiFi) network, and/or the Internet, among others.

[0028] Computing device **140** shown herein is for illustrative purposes only, and variations and modifications are possible without departing from the scope of the present disclosure. For example, the number and types of processors **142**, the number and types of system memories **144**, and/or the number of applications included in the system memory **144** can be modified as desired. Further, the connection topology between the various units in FIG. **1** can be modified as desired. In some embodiments, any combination of the processor(s) **142** and/or the system memory **144** can be included in and/or replaced with any type of virtual computing system, distributed computing system, and/or cloud computing environment, such as a public, private, or a hybrid cloud system.

[0029] Processor(s) **142** receive user input from input devices, such as a keyboard or a mouse. Processor(s) **142** can be any technically feasible form of processing device configured to process data and execute program code. For example, any of processor(s) **142** could be a central processing unit (CPU), a graphics processing unit (GPU), an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), and so forth. In various embodiments any of the operations and/or functions described herein can be performed by processor(s) **142**, or any combination of these different processors, such as a CPU working in cooperation with a one or more GPUs. In various embodiments, the one or more GPU(s) perform parallel processing task, such as matrix multiplications and/or the like in LLM model computations. Processor(s) **142** can also receive user input from input devices, such as a keyboard or a mouse and generate output on one or more displays.

[0030] Similar to memory **114** of compression server **110**, memory **144** of computing device **140** stores content, such as software applications and data, for use by the processor(s) **142**. The system memory **144** can be any type of memory capable of storing data and software applications, such as a RAM, ROM, EPROM, Flash ROM, or any suitable combination of the foregoing. In some embodiments, a storage (not shown) can supplement or replace the system memory **144**. The storage can include any number and type of external memories that are accessible to processor **142**. For example, and without limitation, the storage can include a Secure Digital Card, an external Flash memory, a portable CD-ROM, an optical storage device, a magnetic storage device, and/or any suitable combination of the foregoing.

[0031] To perform inferencing, application **145** accesses retrained compressed LLM model **122**, including the one or more projection matrices **124** and the one or more pre-computed weight matrices **126**, computed by activation compressor **116** from data store **120**. Application **145** then presents input data to retrained compressed LLM model **122** as an activation tensor for a first layer of retrained compressed LLM model **122**. Application **145** then iteratively processes activation tensors layer by layer through retrained compressed LLM model **122** to generate an output. More specifically, for each activation tensor, application **145** multiplies, a respective projection matrix **124** and the respective activation tensor to generate a compressed activation tensor. Application **145** then multiplies a respective pre-computed weight matrix **126** and the compressed activation tensor to generate and, when appropriate further applies an activation function, to generate an output tensor for the respective layer of the retrained compressed LLM model **122**. The output tensor for the respective layer then becomes the activation tensor for the next layer of retrained compressed LLM model **122**. The output tensor of the last layer of retrained compressed LLM model **122** then becomes the output for the retrained compressed LLM model **122**. As described for trained LLM model **118**, retrained compressed LLM model **122** can also be any type of technically feasible machine learning model. For example, in various embodiments, retrained LLM model **122** can be a transformer based LLM model, such as a GPT, with any suitable architecture. The operations performed during inferencing are described in greater detail below in conjunction with FIG. **5-7**.

Compressing a Machine Learning Model

[0032] FIG. **2** illustrates a block diagram of activation compressor **116**, according to various embodiments. As shown, activation compressor **116** includes, without limitation, a calibration module **204** and a retraining module **208**. Calibration module **204** includes, without limitation, a plurality of candidate projection matrices **206**.

[0033] Initially, trained LLM model **118** processes different batches of training data to determine one or more activation tensors **202** for each layer of trained LLM model **118**. Each activation tensor **202** is a multi-dimensional array that represents the outputs of neurons in a corresponding layer of trained LLM model **118** after applying an activation function. In operation, activation compressor **116** uses trained LLM model **118** and one or more activation tensors **202** to generate retrained compressed LLM model **122**, including projection matrices **124** and pre-computed weight matrices **126**.

[0034] Calibration module **204** receives one or more activation tensors **202** and trained LLM model **118** and generates a respective projection matrix **124** for each activation tensor **202**. For a given activation tensor **202**, calibration module **204** performs a series of computations in order to determine respective projection matrix **124** to use when compressing the corresponding layer of trained LLM model **118**. To help obtain an improved compression of trained LLM model **118**, calibration module **204** separately analyzes each activation tensor **202** against a plurality of fidelity metrics. Examples of suitable fidelity metrics include, without limitation, mean squared error (MSE), normalized MSE, general matrix multiplications output-referred MSE (GO-MSE), network loss-referred MSE (NL-MSE), normalized GO-MSE, and normalized NL-MSE.

[0035] The operation of a layer of trained LLM model **118** with an uncompressed activation tensor **202** can be described using the matrix multiplication in equation 1.

$$Y = W^T X \tag{1}$$

where W is a weight matrix of size K×N and X is an input activation tensor of size K×M, such as activation tensor **202**, and output activation tensor Y is of size N×M. Typically, K and N are defined by the LLM model topology and layer instance, which are commonly referred to as embedding or hidden size. For example, a Transformer-based LLM has four layers per block: query-key-value (QKV), projection (Proj), fully connected 1 (FC1), and fully connected 2 (FC2) layers. M is defined by stacking multiple instances of the training data in a two-dimensional (2D) matrix, so that all M instances of the training data can be processed in parallel. For example, the M instances of the training data could represent a batch or multiple batches of the training data.

[0036] Calibration module **204** compresses X in equation 1 by projecting X onto an orthonormal projection matrix P of size K×L, where K is the input activation tensor dimension and depends on the topology and layer instance of trained LLM model **118**, and L is the intermediate dimension. Calibration module **204** can re-expand X using a transpose of P, such that $X \approx PP^T X$. Equation 2 uses associativity of matrix multiplication to approximate the uncompressed activation tensor in equation 1 using P.

$$Y = W^T X \approx W^T PP^T X = W^T(PP^T X) = (P^T W)^T (P^T X) \tag{2}$$

where projection matrix P is not shared across different layers of trained LLM model **118** and each layer of trained LLM model **118** can have a respective projection matrix **124**.

[0037] During inferencing, weight matrix W and projection matrix P in equation 2, are fixed but activation tensor X can change as X depends on the input of trained LLM model **118**. The first term in equation 2, $(P^T W)^T$, can be pre-computed prior to the LLM model being used for inferencing, by multiplying the first term and the second term $(P^T X)$ in equation 2, which is changing with the input. Because projection matrix P is of size K×L, with L<<K, and pre-computed matrix $(P^T W)^T$ is of size L×N, with L<<N, where N is the size of each layer output that matches inputs of the next layer and depends on the topology and layer instance of the trained LLM model **118**, fewer operations are used to compute Y in equation 2 compared to computing Y in equation 1.

[0038] FIG. **3** illustrates computations of a compressed activation tensor **202**, according to various embodiments. As shown, projection matrix P is used to compress activation tensor X. As described in FIG. **2**, the output activation tensor Y with size of N×M is represented as $W^T(PP^T X)$, where M is defined by stacking multiple instances of the training data in a two-dimensional (2D) matrix, so that all M instances of the training data can be processed in parallel. For example, the M instances of the training data could represent a batch or multiple batches of the training data.

[0039] Referring back to FIG. **2**, in order to perform the compression, calibration module **204** uses projection matrix P to approximate activation tensor X as $\tilde{X} = PP^T X$. For a vector $x \in X$, the counterpart in $\tilde{x} \in \acute{X}$ is given by equation 3.

$$\tilde{x} = \sum_{i=1}^{L} \langle p_i, x \rangle p_i \tag{3}$$

where $\{p_i\}_{i=1}^{L}$ are the orthonormal column vectors of P, i.e., $\langle p_i, p_j \rangle = 1_{(i==j)}$, $\forall i, j \in 1 \ldots L$. Compressing using projection matrix P introduces an approximation error because $X \neq PP^T X$ due to $PP^T \neq I_{K \times K}$, where $I_{K \times K}$ is the K×K identity matrix. In some embodiments, calibration module **204** uses different fidelity metrics to measure the approximation error. For each fidelity metric, calibration module **204** computes a respective candidate projection matrix P that minimizes the measured approximation error computed using that fidelity metric. For example, when calibration module **204** uses the MSE fidelity metric, the resulting approximation error is computed according to equation 4. And when calibration module **204** uses the NMSE fidelity metric, the resulting approximation error is computed according to equation 5.

$$E\left[\|x - \tilde{x}\|^2\right] \tag{4}$$

$$E\left[\|x - \tilde{x}\|^2 / \|x\|^2\right] \tag{5}$$

[0040] In some embodiments, calibration module **204** can measure approximation error for the output activation tensor $y \in Y$. The output activation tensor y is defined as $y = \langle w, x \rangle$ for weight vector $w \in W$ and activation vector $x \in X$. Calibration module **204** considers $\tilde{y}$ to be the output activation tensor when activation tensor **202** is approximated by equation 2. Similarly, $\tilde{y}$ is given by $\tilde{y} = \langle w, x \rangle$, where x is defined in equation 3. Therefore, when calibration module **204** uses the GO-MSE fidelity metric, the resulting approximation error is computed according to equation 6. Alternatively, calibration module **204** can use upper bounds of the GO-MSE fidelity metric defined in equation 7 as a proxy to measure the output approximation error. In some embodiments, calibration module **204** can also measure the output approximation error for the normalized GO-MSE fidelity metric.

$$\mathbb{E}\left[(y-\tilde{y})^2\right] \tag{6}$$

$$\mathbb{E}\left[(y-\tilde{y})^2\right] \leq 2\mathbb{E}\left[\|w\|^2 \cdot \|x\|^2\right] - 2\mathbb{E}[\langle w, x\rangle \cdot \langle w, \tilde{x}\rangle] \tag{7}$$

[0041] In some embodiments, calibration module **204** can measure approximation error for trained LLM model **118** loss. Given an input to trained LLM model **118**, the output loss $\mathcal{L}$ can be defined by any loss function, such as a vocab cross-entropy. When an activation tensor **202** is approximated by equation 3, calibration module **204** considers $\tilde{\mathcal{L}}$ as the computed loss for trained LLM model **118** with the approximated activation tensor. When calibration module **204** uses the NL-MSE fidelity metric, the resulting approximation error is computed according to equation 8. In some embodiments, calibration module **204** can also measure loss approximation error for normalized NL-MSE fidelity metric. Alternatively, when calibration module **204** uses the upper bounds of NL-MSE fidelity metric, the resulting approximation error is computed according to equation 9 as a proxy to measure the loss approximation error.

$$\mathbb{E}\left[(\mathcal{L}-\tilde{\mathcal{L}})^2\right] \tag{8}$$

$$\mathbb{E}\left[(\mathcal{L}-\tilde{\mathcal{L}})^2\right] \leq 2\mathbb{E}\left[\|\nabla_x\|^2 \cdot \|x\|^2\right] - 2\mathbb{E}[\langle \nabla_x, x\rangle \cdot \langle \nabla_x, \tilde{x}\rangle] \tag{9}$$

where a first order Taylor approximation on the loss function is used and the gradient with respect to vector x is denoted as ∇_x.

[0042] To minimize each of the described fidelity metrics, calibration module **204** computes a corresponding auto-correlation matrix. For example, for the MSE fidelity metric in equation 4, calibration module **204** uses a randomly selected activation vector x from activation tensor **202** to generate an activation auto-correlation matrix of size K×K as $C_X=\mathbb{E}\,[xx^T]$ where expectation is taken over activation vectors. The auto-correlation matrix can be empirically estimated by equation 10 using M activation vectors x_i (collectively X) from activation tensor **202**.

$$X = [x_1|\ \ldots\ |x_M] \Rightarrow XX^T = \left[x_1x_1^T + \ldots + x_Mx_M^T\right] \Rightarrow C_X = xx^T/M \tag{10}$$

[0043] Alternatively, calibration module **204** can compute the auto-correlation corresponding to the NMSE fidelity metric in equation 5. In such a case, for an activation tensor X, the auto-correlation for NMSE fidelity metric is computed by equation 11.

$$\hat{C}_X = \mathbb{E}\left[(x/\|x\|)(x/\|x\|)^T\right] \tag{11}$$

[0044] To minimize the approximation error, calibration module **204** can also compute the auto-correlation matrix for the upper bounds of the GO-MSE fidelity metric and the upper bounds of the NL-MSE fidelity metric defined in equations 7 and 9 and the upper bounds of the normalized GO-MSE fidelity metric, and the upper bounds of the normalized NL-MSE fidelity metric. In such cases, for a given activation tensor X, the auto-correlation matrix can be computed by equations 12-15 for the upper bounds of the GO-MSE fidelity metric, the upper bounds of the NL-MSE fidelity metric, the normalized upper bounds of the GO-MSE fidelity metric, and the normalized upper bounds of the NL-MSE fidelity metric, respectively.

$$C = \mathbb{E}\left[xx^Tww^T + ww^Txx^T\right] \tag{12}$$

$$C = \mathbb{E}\left[xx^T\nabla_x\nabla_x^T + \nabla_x\nabla_x^Txx^T\right] \tag{13}$$

$$\hat{C} = \mathbb{E}\left[(xx^Tww^T + ww^Txx^T)/\|w\|^2 \cdot \|x\|^2\right] \tag{14}$$

$$\hat{C} = \mathbb{E}\left[\frac{(xx^T\nabla_x\nabla_x^T + \nabla_x\nabla_x^Txx^T)}{\|\nabla_x\|^2 \cdot \|x\|^2}\right] \tag{15}$$

[0045] For a given activation tensor **202**, calibration module **204** selects a respective fidelity metric and computes the respective auto-correlation matrices using equation 10 for multiple batches of activation tensors **202**. Accordingly, calibration module **204** uses M randomly selected activation vectors xi (collectively X), for each batch of activation tensors **202** among B batches that were randomly selected from activation tensors **202** to estimate a respective auto-correlation matrix for a given activation tensor **202**. For example, the auto-correlation matrices for the MSE fidelity metric are computed using $C_X^{(j)}=x_i^{(j)}x_i^{(j)T}/M$, where superscript j denotes the batch index. Then, calibration module **204** estimates a respective auto-correlation matrix for the given activation tensor **202** by aggregating the computed auto-correlation matrices, e.g., averaging the computed auto-correlation matrices $C_X=\Sigma_{j=1}^{B}C_x^{(j)}/B$.

[0046] After computing the estimated auto-correlation matrix C_X, calibration module **204** computes respective eigenvectors of the estimated auto-correlation matrix C_X. Calibration module **204** then generates the candidate projection matrix P for the activation tensor and fidelity metric pair using the eigenvectors. Because C_X is symmetric, positive, and semi-definite matrix having a real eigenvalue decomposition (EVD) $C_X=VDV^T$ where V is an orthonormal matrix whose columns are eigenvectors, and D is a diagonal matrix containing the corresponding non-negative eigenvalues, assumed to be sorted in decreasing order. The eigenvector corresponding to the i^{th} largest eigenvalue is called i^{th} principal eigenvector. For an activation tensor **202** whose auto-correlation matrix has an eigenvalue decomposition given by $C_x=VDV^T$, the projection matrix P minimizing the fidelity metrics in equations 4, 5, 7, 9 is given by equation 16.

$$P = [v_1|\ \ldots\ |v_L] \tag{16}$$

where v_i is the i^{th} principal eigenvector in V.

[0047] Calibration module **204** performs similar computations for each of the remaining fidelity metrics to generate a set of candidate projection matrices for a given activation tensor **202**. More specifically, for the given activation tensor **202** and for a given fidelity metric, calibration module **204** repeats computing the respective autocorrelation matrices using equation 10 for multiple batches of activation tensors **202** randomly selected from activation tensors **202** computing an auto-correlation matrix for each batch, estimating an auto-correlation matrix by aggregating the computed auto-correlation matrices of different batches, computing an eigenvector decomposition for estimated auto-correlation matrix and generating a candidate projection matrix for the given fidelity metric.

[0048] For each activation tensor **202** and fidelity metric pair, calibration module **204** then multiplies respective candidate projection matrix **206** and the given activation tensor **202** to generate a compressed activation tensor. Calibration module **204** then multiplies the respective candidate projection matrix **206** and the weight matrix corresponding to the given activation tensor **202** to generate a respective partially compressed LLM model where only the layer associated with the activation tensor **202** is compressed and the remaining layers are not. Calibration module **204** then selects a projection matrix **124** from among respective candidate projection matrices **206** that corresponds to the respective partially compressed LLM model with the highest evaluated performance. To evaluate the performance, the respective partially compressed LLM model processes evaluation data to generate inferencing results. Evaluation data can be a subset of the training data, or any other data not presented to the trained LLM model **118**. Calibration module **204** then uses a performance metric to evaluate the inferencing results. Calibration module **204** can use any metric to evaluate the performance of the partially compressed LLM model, such as the Perplexity score. Perplexity score measures a neural model's ability to make good predictions for new input patterns that were not included in the training data. Perplexity score is computed based on the respective partially compressed LLM model understanding of the text. The partially respective partially compressed LLM model assigns a probability to each possible next word in an output sentence. Then perplexity is calculated as the inverse of the geometric mean of the probabilities.

[0049] Calibration module **204** then repeats, for each of the remaining activation tensors **202**, the steps to generate respective candidate projection matrices **206** for each of the fidelity metrics. Calibration module **204** then selects, for each of the remaining activation tensors **202**, a respective projection matrix **124**.

[0050] Retraining module **208** receives projection matrices **124** generated by calibration module **204** and trained LLM model **118**. Retraining module **208** then uses activation tensors **202** and projection matrices **124** to finish generating retrained compressed LLM model **122**, including pre-computed weight matrices **126**. For each activation tensor **202**, retraining module **208** multiplies the respective projection matrix **124** and the weight matrix corresponding to activation tensor **202**. Retraining module **208** then retrains the compressed LLM model while keeping the respective projection matrices **124** static. During retraining, retraining module **208** modifies the weight matrices of the compressed LLM model to improve the performance of the compressed LLM model. Any performance metric can be used by retraining module **208**, such as the Perplexity score. Retraining module **208** can use any feasible training technique to retrain the compressed LLM model, such as backpropagation. After completing the retraining of the compressed LLM model, retraining module **208** computes the respective pre-computed weight matrices **126** by multiplying selected projection matrices **124** and the weight matrices of retrained LLM model corresponding to each activation tensor **202**. Retraining module **208** then stores retrained compressed LLM model **122**, including projection matrices **124** and pre-computed weight matrices **126**, into data store **120** to be used in any suitable application, such as application **145**.

[0051] FIGS. **4**A and **4**B are a flow diagram of method steps for compressing trained LLM model **118**, according to various embodiments. Although the method steps are described in conjunction with the systems of FIGS. **1-3**, persons skilled in the art will understand that any system configured to perform the method steps in any order falls within the scope of the various embodiments.

[0052] As shown, a method **400** begins at step **402**, where compression server **110** accesses trained LLM model **118**. Trained LLM model **118** can be any type of machine learning model. For example, in various embodiments, trained LLM model **118** can be a transformer based LLM model, such as a GPT, with any suitable architecture. In some embodiments, compression server **110** can access any number of trained LLM models. Compression server **110** can receive trained LLM model **118** from any storage device, such as data store **120**.

[0053] At step **404**, compression server **110** accesses different batches of the training data. In some embodiments, compression server **110** can receive different batches of the training data from any storage device, such as data store **120**.

[0054] At step **406**, compression server **110** runs different batches of the training data through trained LLM model **118** to determine activation tensors **202** for each layer of trained LLM model **118**.

[0055] At step **408**, for each activation tensor **202** and using different fidelity metrics, calibration module **204** computes respective auto-correlation matrices corresponding to each activation tensor **202** and fidelity metric pair using different batches of the training data. Calibration module **204** separately analyzes each activation tensor **202** against a plurality of fidelity metrics to improve compression of trained LLM model **118**. Examples of suitable fidelity metrics include, without limitation, MSE, NMSE, GO-MSE, NL-MSE, normalized GO-MSE, and normalized NL-MSE. To minimize each of the described fidelity metrics, calibration module **204** computes a corresponding auto-correlation matrix. For example, for the MSE fidelity metric in equation 4, calibration module **204** uses a randomly selected activation vector x from activation tensor **202** to generate an activation auto-correlation matrix of size K×K as $C_X = \mathbb{E}[xx^T]$, where expectation is taken over the activation vectors. The auto-correlation matrix can be empirically estimated by equation 10 using M activation vectors xi (collectively X) from activation tensor **202**. Calibration module **204** then repeats computing the respective auto-correlation matrices for multiple batches of activation tensors **202**. For example, the auto-correlation matrices for the MSE fidelity metric are computed using $C_X^{(j)} = x_i^{(j)} x_i^{(j)T}/M$, where superscript j denotes batch index. Alternatively, calibration module **204** can compute the auto-correlation corresponding to the NMSE fidelity metric in equation 5. In such a case, for an activation tensor X, the auto-correlation for NMSE fidelity metric is computed by equation 11. To minimize the approximation error, calibration module **204** can also compute the auto-correlation matrix for the upper bounds of the GO-MSE fidelity metric and the upper bounds of the NL-MSE fidelity metric defined in equations 7 and 9 and the upper bounds of the normalized GO-MSE fidelity metric, and the upper bounds of the normalized NL-MSE fidelity metric. In such cases, for a given activation tensor X, the auto-correlation matrix can be computed by equations

12-15 for the upper bounds of the GO-MSE fidelity metric, the upper bounds of the NL-MSE fidelity metric, the normalized upper bounds of the GO-MSE fidelity metric, and the normalized upper bounds of the NL-MSE fidelity metric, respectively. Calibration module **204** performs similar computations for each of the remaining activation tensor **202** and fidelity metric pairs to compute a set of respective auto-correlation matrices for a given activation tensor **202** and fidelity metric pair.

[0056] At step **410**, for each activation tensor **202** and fidelity metric pair, calibration module **204** computes a respective estimated auto-correlation matrix corresponding to activation tensor **202** by averaging the respective auto-correlation matrices computed for each activation tensor **202** and fidelity metric pair. Calibration module **204** estimates a respective auto-correlation matrix for the given activation tensor **202** and a given fidelity metric by aggregating the computed auto-correlation matrices, e.g., averaging the computed auto-correlation matrices for the selected B batches $C_X=\Sigma_{j=1}^{B}C_x^{(j)}/B$. Calibration module **204** performs similar computations for each of the remaining activation tensor **202** and fidelity metric pairs to create a respective auto-correlation matrix estimate for a given activation tensor **202** and fidelity metric pair.

[0057] At step **412**, for each activation tensor **202** and fidelity metric pair, calibration module **204** computes respective eigenvectors of respective estimated auto-correlation matrix corresponding to activation tensor **202** and fidelity metric pair. After computing the estimated auto-correlation matrix C_X, calibration module **204** computes respective eigenvectors of each estimated auto-correlation matrix C_X. Because C_X is symmetric, positive, and semi-definite matrix having a real eigenvalue decomposition (EVD) $C_X=VDV^T$ where V is an orthonormal matrix whose columns are eigenvectors, and D is a diagonal matrix containing the corresponding non-negative eigenvalues, assumed to be sorted in decreasing order. The eigenvector corresponding to the i^{th} largest eigenvalue is called i^{th} principal eigenvector. For an activation tensor **202** and fidelity metric pair whose auto-correlation matrix has an eigenvalue decomposition given by $C_X=VDV^T$, the eigenvectors minimizing the fidelity metrics in equations 4, 5, 7, 9 are $[v_1|, \ldots, |v_L]$, where v_i is the i^{th} principal eigenvector in V. Calibration module **204** performs similar computations for each of the activation tensor **202** and fidelity metric pairs to create a set of eigenvectors for each activation tensor **202** and fidelity metric pair.

[0058] At step **414**, for each activation tensor **202** and using different fidelity metrics, calibration module **204** generates a respective candidate projection matrix using respective eigenvectors of the respective estimated auto-correlation matrix corresponding to activation tensor **202** and fidelity metric pair. For each activation tensor **202** and each respective fidelity metric, calibration module **204** uses the computed eigenvectors at step **412** to generate the respective candidate projection matrix P using equation 16. Calibration module **204** performs similar computations for each of the activation tensor **202** and fidelity metric pairs to create a candidate projection matrix for a given activation tensor **202** and fidelity metric pair.

[0059] At step **416**, for each activation tensor **202** and using different fidelity metrics, calibration module **204** multiplies respective candidate projection matrix **206** and activation tensor **202** and the weight matrix corresponding to each activation tensor **202** to generate the respective partially compressed trained LLM model. Calibration module **204** performs similar computations for each of the activation tensor **202** and fidelity metric pairs to create a respective partially compressed trained LLM model for each activation tensor **202** and fidelity metric pair.

[0060] At step **418**, for each activation tensor **202**, calibration module **204** selects a projection matrix from the respective candidate projection matrices **206** corresponding to activation tensor **202** that corresponds to the respective partially compressed LLM model with the highest evaluated performance. To evaluate the performance, the respective partially compressed LLM model processes evaluation data to generate inferencing results. Evaluation data can be a subset of the training data, or any other data not presented to trained LLM model **118**. Calibration module **204** then uses a performance metric to evaluate inferencing results. Calibration module **204** can use any metric to evaluate the performance of the partially compressed LLM model, such as the Perplexity score.

[0061] At step **420**, for each activation tensor **202**, retraining module **208** multiplies the selected projection matrix **124** corresponding to activation tensor **202** and the weight matrix corresponding to activation tensor **202** to compress trained LLM model **118** according to equation 2. Retraining module **208** performs similar computations for each of the activation tensors **202**.

[0062] At step **422**, for each activation tensor **202**, retraining module **208** retrains the weight matrix corresponding to activation tensor **202**, while keeping projection matrix **124** corresponding to activation tensor **202** static, to retrain the compressed LLM model. During retraining, retraining module **208** modifies the weight matrices of the compressed LLM model to improve the performance of the compressed LLM model. Any performance metric of loss function of retraining module **208** can be used by retraining module **208**, such as the Perplexity score. Retraining module **208** can use any feasible training technique to retrain the compressed LLM model, such as backpropagation.

[0063] At step **424**, for each activation tensor **202**, retraining module **208** computes the pre-computed weight matrix **126** corresponding to activation tensor **202** by multiplying projection matrix **124** corresponding to activation tensor **202** and the retrained weight matrix corresponding to activation tensor **202**. Retraining module **208** uses the first term in equation 2, P^TW, to compute each pre-computed weight matrix **126**. In some embodiments, retraining module **208** stores retrained compressed LLM model **122**, including projection matrices **124** and pre-computed weight matrices **126** in data store **120** to be used in any suitable application, such as application **145**.

Inferencing Using a Compressed a Machine Learning Model

[0064] FIG. **5** illustrates application **145** in more detail, according to various embodiments. In operation, application **145** receives input data **502** and performs inferencing to generate output **504**. Input data **502** can be various forms of text and structured data, such as natural language text, code, tables, structured text, and/or the like. Output **504** can be any type of machine learning model output, such as natural language text, structured text, code, and/or the like.

[0065] Application **145** accesses retrained compressed LLM model **122**, including the one or more projection matrices **124** and the one or more pre-computed weight matrices **126**, from data store **120**. To perform inferencing, application **145** presents input data **502** to retrained compressed LLM model **122** as an activation tensor X to the first layer of retrained compressed LLM model **122**. Application **145** compresses activation tensor X using the projection matrix **124** for the first layer of retrained LLM model **122** by multiplying the projection matrix **124** and the activation tensor X. Application **145** then multiplies the pre-computed weight matrix **126** and the compressed activation tensor for the first layer according to equation 2 and then, when appropriate, further applies an activation function to generate an output tensor Y for the first layer of retrained compressed LLM model **122**. Output tensor Y for the first layer then becomes the activation tensor X for the second layer. Application **145** then applies equation 2 and, when appropriate, an activation function to the activation tensor X for the second layer of retrained compressed LLM model **122** to generate an output tensor Y for the second layer. Application **145** repeats the process for each of the remaining layers of retrained compressed LLM model **122** until output **504** is generated by the final layer of retrained compressed LLM model **122**.

[0066] Although the inferencing process of application **145** is described above with respect to input data **502** having a single input vector, multiple input vectors M can be stacked to form an input matrix. For example, the M instances of input data **502** could represent a batch or multiple batches of input data **502**. In such embodiments, the stacked input vectors of the input matrix can be processed in parallel using the same iterative application of equation 2 with the respective projection matrix **124** and respective pre-computed weight matrix **126** at each layer of retrained compressed LLM model **122** to generate output **504** as a matrix of M outputs. Exemplary operations performed by application **145** to compress the activation tensor X at each layer of retrained compressed LLM model **122** are shown below in conjunction with FIG. **6**.

[0067] FIG. **6** illustrates computations of a respective activation tensor Y for a layer of retrained compressed LLM model **122** during inferencing, according to various embodiments. As shown, during inferencing, for a given layer of retrained compressed LLM model **122**, pre-computed weight matrix **126** and projection matrix **124** are used to compress the activation tensor X. As described in equation 2, the output activation tensor Y with size of N×M is represented as $(P^TW)^T(P^TX)$, where N is the size of each layer output that becomes the input of the next layer and depends on the topology and layer instance of retrained compressed LLM model **122**, and M is the number of stacked instances of input data **502** In some embodiments, M can represent one input data **502**. Projection matrix P in equation 2 has the size of K×L, where K is the input activation tensor dimension and depends on the topology and layer instance of trained LLM model **118**, and L is the intermediate dimension. Because projection matrix P is of size K×L, and L<<K, fewer operations are used to compute Y in equation 2 compared to computing Y in equation 1. For example, if N=K, and L=K/4, then compressed retrained LLM model **504** can yield a 50 percent compression at inference time.

[0068] FIG. **7** is a flow diagram of method steps for compressing and executing retrained compressed LLM model **122**, according to various embodiments. Although the method steps are described in conjunction with the systems of FIGS. **1-6**, persons skilled in the art will understand that any system configured to perform the method steps in any order falls within the scope of the various embodiments

[0069] As shown, a method **700** begins at step **702**, where for each activation tensor X in retrained compressed LLM model **122**, application **145** accesses pre-computed weight matrix **126** and projection matrix **124** corresponding to activation tensor X. Application **145** initially accesses retrained compressed LLM model **122**, projection matrix **124**, and pre-computed weight matrix **126** corresponding to activation tensor X from data store **120**. Retrained compressed LLM model **122** can be any type of machine learning model. For example, in various embodiments, retrained compressed LLM model **122** can be a transformer based LLM model, such as a GPT, with any suitable architecture. In some embodiments, application **145** can access any number of retrained compressed LLM models **122**. Application **145** can receive retrained compressed LLM model **122**, projection matrices **124**, and pre-computed weight matrices **126** corresponding to activation tensor X from any storage device, such as data store **120**.

[0070] At step **704**, application **145** receives input data **502**. Input data **502** can be various forms of text and structured data, such as natural language text, code, tables, structured text, and/or the like. In some scenarios input data **502** can be a single input vector or a stack of M input vectors. For example, the M instances of input data **502** could represent a batch or multiple batches of input data **502**.

[0071] At step **706**, for each layer in retrained compressed LLM model **122**, application **145** compresses the respective activation tensor using the respective projection matrix **126** and generates a respective output tensor based on the respective pre-computed weight matrix **124** and the compressed respective activation tensor. Application **145** presents input data **502** to retrained compressed LLM model **122** as an activation tensor X to the first layer of retrained compressed LLM model **122**. Application **145** compresses activation tensor X using the projection matrix **124** for the first layer of retrained compressed LLM model **122** by multiplying the projection matrix **124** for the first layer and activation tensor X. Application **145** then multiplies the pre-computed weight matrix **126** and the compressed activation tensor for the first layer and, when appropriate, further applies an activation function to generate an output tensor Y for the first layer of retrained compressed LLM model **122**. Output tensor Y for the first layer then becomes the activation tensor X for the second layer. Application **145** then applies equation 2 and, when appropriate, an activation function to the activation tensor X for the second layer of retrained compressed LLM model **122** to generate an output tensor Y for the second layer. Application **145** then repeats the process for each of the remaining layers of retrained compressed LLM model **122** until output **504** is generated by the final layer of retrained compressed LLM model **122**. When input data **502** includes a stack of M input data, the stacked input vectors of the input matrix can be processed in parallel using the same iterative application of equation 2 with the respective projection matrix **124** and respective pre-computed weight matrix **126** at each layer of retrained compressed LLM model **122** to generate output **504** as a matrix of M outputs.

[0072] At step **708**, application **145** provides output **504**. Output **504** is generated by the final layer of retrained compressed LLM model **122**. Output **504** can be any type of machine learning model output, such as natural language text, structured text, code, and/or the like.

[0073] FIG. **8** is a more detailed illustration of compression server **110** of FIG. **1**, according to the various embodiments. Compression server **110** can be any type of computing device, including, without limitation, a server machine, a server platform, a desktop machine, a laptop machine, a hand-held/mobile device, a digital kiosk, an in-vehicle infotainment system, and/or a wearable device. In some embodiments, compression server **110** is a server machine operating in a data center or a cloud computing environment that provides scalable computing resources as a service over a network.

[0074] As shown, the compression server **110** includes, without limitation, processor(s) **112** and system memory(ies) **114** coupled to a parallel processing subsystem **812** via a memory bridge **814** and a communication path **813**. Memory bridge **814** is further coupled to an I/O (input/output) bridge **820** via a communication path **807**, and I/O bridge **820** is, in turn, coupled to a switch **826**.

[0075] In various embodiments, I/O bridge **820** is configured to receive user input information from optional input devices **818**, such as a keyboard, mouse, touch screen, sensor data analysis (e.g., evaluating gestures, speech, or other information about one or more uses in a field of view or sensory field of one or more sensors), and/or the like, and forward the input information to the processor(s) **112** for processing. In some embodiments, compression server **110** is a server machine in a cloud computing environment. In such embodiments, compression server **110** does not include input devices **818**, but can receive equivalent input information by receiving commands (e.g., responsive to one or more inputs from a remote computing device) in the form of messages transmitted over a network and received via the network adapter **830**. In some embodiments, switch **826** is configured to provide connections between I/O bridge **820** and other components of compression server **110**, such as a network adapter **830** and various add-in cards **824** and **828**.

[0076] In some embodiments, I/O bridge **820** is coupled to a system disk **822** that is configured to store content and applications and data for use by processor(s) **112** and parallel processing subsystem **812**. In one embodiment, system disk **822** provides non-volatile storage for applications and data and can include fixed or removable hard disk drives, flash memory devices, and CD-ROM (compact disc read-only-memory), DVD-ROM (digital versatile disc-ROM), Blu-ray, HD-DVD (high-definition DVD), or other magnetic, optical, or solid state storage devices. In various embodiments, other components, such as universal serial bus or other port connections, compact disc drives, digital versatile disc drives, film recording devices, and the like, can be connected to I/O bridge **820** as well.

[0077] In various embodiments, memory bridge **814** is a Northbridge chip, and I/O bridge **820** is a Southbridge chip. In addition, communication paths **807** and **813**, as well as other communication paths within compression server **110**, can be implemented using any technically suitable protocols, including, without limitation, AGP (Accelerated Graphics Port), HyperTransport, or any other bus or point-to-point communication protocol known in the art.

[0078] In some embodiments, parallel processing subsystem **812** comprises a graphics subsystem that delivers pixels to an optional display device **816** that can be any conventional cathode ray tube, liquid crystal display, light-emitting diode display, and/or the like. In such embodiments, the parallel processing subsystem **812** incorporates circuitry optimized for graphics and video processing, including, for example, video output circuitry. Such circuitry can be incorporated across one or more parallel processing units (PPUs), also referred to herein as parallel processors, included within the parallel processing subsystem **812**.

[0079] In some embodiments, the parallel processing subsystem **812** incorporates circuitry optimized (e.g., that undergoes optimization) for general purpose and/or compute processing. Again, such circuitry can be incorporated across one or more PPUs included within parallel processing subsystem **812** that are configured to perform such general purpose and/or compute operations. In yet other embodiments, the one or more PPUs included within parallel processing subsystem **812** is configured to perform graphics processing, general purpose processing, and/or compute processing operations. Memory **114** includes at least one device driver configured to manage the processing operations of the one or more PPUs within parallel processing subsystem **812**. Illustratively, memory **114** includes, without limitation, activation compressor **116** and trained LLM model **118**.

[0080] In various embodiments, parallel processing subsystem **812** is integrated with one or more of the other elements of FIG. **8** to form a single system. For example, parallel processing subsystem **812** can be integrated with processor **112** and other connection circuitry on a single chip to form a system on a chip (SoC).

[0081] In some embodiments, communication path **813** is a PCI Express link, in which dedicated lanes are allocated to each PPU. Other communication paths may also be used. The PPU advantageously implements a highly parallel processing architecture, and the PPU may be provided with any amount of local parallel processing memory (PP memory).

[0082] It will be appreciated that the system shown herein is illustrative and that variations and modifications are possible. The connection topology, including the number and arrangement of bridges, the number of processors **112**, and the number of parallel processing subsystems **812**, can be modified as desired. For example, in some embodiments, system memory **114** is connected to the processor(s) **112** directly rather than through memory bridge **814**, and other devices communicate with system memory **114** via memory bridge **814** and processor **112**. In other embodiments, parallel processing subsystem **812** is connected to I/O bridge **820** or directly to processor **112**, rather than to memory bridge **814**. In still other embodiments, I/O bridge **820** and memory bridge **814** are integrated into a single chip instead of existing as one or more discrete devices. In certain embodiments, one or more components shown in FIG. **8** may not be present. For example, switch **826** could be eliminated, and network adapter **830** and add-in cards **824**, **828** would connect directly to I/O bridge **820**. Lastly, in certain embodiments, one or more components shown in FIG. **8** are implemented as virtualized resources in a virtual computing environment, such as a cloud computing environment. In particular, the parallel processing subsystem **812** can be implemented as a virtualized parallel processing subsystem in at least one embodiment. For example, the parallel processing subsystem **812** can be implemented as a virtual graphics processing unit(s) (vGPU(s)) that renders graphics on a virtual machine(s) (VM(s)) executing on a server machine(s) whose GPU(s) and other physical resources are shared across one or more VMs.

[0083] FIG. **9** is a more detailed illustration of computing device **140** of FIG. **1**, according to the various embodiments. Computing device **140** can be any type of computing device, including, without limitation, a server machine, a server platform, a desktop machine, a laptop machine, a hand-held/mobile device, a digital kiosk, an in-vehicle infotainment system, and/or a wearable device. In some embodiments, computing device **140** is a server machine operating in a data center or a cloud computing environment that provides scalable computing resources as a service over a network.

[0084] As shown, computing device **140** includes, without limitation, processor(s) **142** and system memory(ies) **144** coupled to a parallel processing subsystem **912** via a memory bridge **914** and a communication path **913**. Memory bridge **914** is further coupled to an I/O (input/output) bridge **920** via a communication path **907**, and I/O bridge **920** is, in turn, coupled to a switch **926**.

[0085] In various embodiments, I/O bridge **920** is configured to receive user input information from optional input devices **918**, such as a keyboard, mouse, touch screen, sensor data analysis (e.g., evaluating gestures, speech, or other information about one or more uses in a field of view or sensory field of one or more sensors), and/or the like, and forward the input information to the processor(s) **142** for processing. In some embodiments, computing device **140** is a server machine in a cloud computing environment. In such embodiments, computing device **140** does not include input devices **918**, but can receive equivalent input information by receiving commands (e.g., responsive to one or more inputs from a remote computing device) in the form of messages transmitted over a network and received via the network adapter **930**. In some embodiments, switch **926** is configured to provide connections between I/O bridge **920** and other components of computing device **140**, such as a network adapter **930** and various add-in cards **924** and **928**.

[0086] In some embodiments, I/O bridge **920** is coupled to a system disk **922** that is configured to store content and applications and data for use by processor(s) **142** and parallel processing subsystem **912**. In one embodiment, system disk **922** provides non-volatile storage for applications and data and can include fixed or removable hard disk drives, flash memory devices, and CD-ROM (compact disc read-only-memory), DVD-ROM (digital versatile disc-ROM), Blu-ray, HD-DVD (high-definition DVD), or other magnetic, optical, or solid state storage devices. In various embodiments, other components, such as universal serial bus or other port connections, compact disc drives, digital versatile disc drives, film recording devices, and the like, can be connected to I/O bridge **920** as well.

[0087] In various embodiments, memory bridge **914** is a Northbridge chip, and I/O bridge **920** is a Southbridge chip. In addition, communication paths **907** and **913**, as well as other communication paths within computing device **140**, can be implemented using any technically suitable protocols, including, without limitation, AGP (Accelerated Graphics Port), HyperTransport, or any other bus or point-to-point communication protocol known in the art.

[0088] In some embodiments, parallel processing subsystem **912** comprises a graphics subsystem that delivers pixels to an optional display device **916** that can be any conventional cathode ray tube, liquid crystal display, light-emitting diode display, and/or the like. In such embodiments, the parallel processing subsystem **912** incorporates circuitry optimized for graphics and video processing, including, for example, video output circuitry. Such circuitry can be incorporated across one or more parallel processing units (PPUs), also referred to herein as parallel processors, included within the parallel processing subsystem **912**.

[0089] In some embodiments, the parallel processing subsystem **912** incorporates circuitry optimized (e.g., that undergoes optimization) for general purpose and/or compute processing. Again, such circuitry can be incorporated across one or more PPUs included within parallel processing subsystem **912** that are configured to perform such general purpose and/or compute operations. In yet other embodiments, the one or more PPUs included within parallel processing subsystem **912** is configured to perform graphics processing, general purpose processing, and/or compute processing operations. Memory **144** includes at least one device driver configured to manage the processing operations of the one or more PPUs within parallel processing subsystem **912**. Illustratively, memory **144** includes, without limitation, application **145**.

[0090] In various embodiments, parallel processing subsystem **912** is integrated with one or more of the other elements of FIG. **9** to form a single system. For example, parallel processing subsystem **912** can be integrated with processor **142** and other connection circuitry on a single chip to form a system on a chip (SoC).

[0091] In some embodiments, communication path **913** is a PCI Express link, in which dedicated lanes are allocated to each PPU. Other communication paths may also be used. The PPU advantageously implements a highly parallel processing architecture, and the PPU may be provided with any amount of local parallel processing memory (PP memory).

[0092] It will be appreciated that the system shown herein is illustrative and that variations and modifications are possible. The connection topology, including the number and arrangement of bridges, the number of processors **142**, and the number of parallel processing subsystems **912**, can be modified as desired. For example, in some embodiments, system memory **144** is connected to the processor(s) **142** directly rather than through memory bridge **914**, and other devices communicate with system memory **144** via memory bridge **914** and processor **142**. In other embodiments, parallel processing subsystem **912** is connected to I/O bridge **920** or directly to processor **142**, rather than to memory bridge **914**. In still other embodiments, I/O bridge **920** and memory bridge **914** are integrated into a single chip instead of existing as one or more discrete devices. In certain embodiments, one or more components shown in FIG. **9** may not be present. For example, switch **926** could be eliminated, and network adapter **930** and add-in cards **924**, **928** would connect directly to I/O bridge **920**. Lastly, in certain embodiments, one or more components shown in FIG. **9** are implemented as virtualized resources in a virtual computing environment, such as a cloud computing environment. In particular, the parallel processing subsystem **912** can be implemented as a virtualized parallel processing subsystem in at least one embodiment. For example, the parallel processing subsystem **912** can be implemented as a virtual graphics processing unit(s) (vGPU(s)) that renders graphics on a virtual machine(s) (VM(s)) executing on a server machine(s) whose GPU(s) and other physical resources are shared across one or more VMs.

[0093] In sum, techniques have been described for compressing LLM models by compressing the activation tensors of the LLM models. The described techniques include, a trained LLM model processing different batches of training data to determine activation tensors for each layer of the trained LLM model. The described techniques further include applying different fidelity metrics for each activation tensor to determine projection matrices to compress the trained LLM model. For each activation tensor and fidelity metric pair, multiple steps are performed, a first step computes respective auto-correlation matrices for different batches of training data, a second step computes a respective estimated auto-correlation matrix by averaging the respective auto-correlation matrices, a third step computes respective eigenvectors of the respective estimated auto-correlation matrix, a fourth step generates a respective projection matrix using the respective eigenvectors, and a fifth step multiplies the respective projection matrix to the activation tensor and multiples the respective projection matrix and a weight matrix corresponding to the activation tensor to generate a respective partially compressed trained LLM model. Then, for each activation tensor, the techniques include selecting a projection matrix from the respective projection matrices that corresponds to the respective partially compressed LLM model with the highest evaluated performance, compressing the trained LLM model using the selected projection matrices, retraining the weight matrices of the compressed LLM model while keeping the projection matrix static to retrain the compressed LLM model, and computing a pre-computed weight matrices by multiplying the selected projection matrices and corresponding retrained weight matrices. During inferencing, the techniques include presenting input data as an activation tensor for a first layer of the retrained LLM model and then iteratively compressing the activation tensors and applying the pre-computed weight matrices layer by layer to generate an output. More specifically, for each respective activation tensor, a respective projection matrix and the respective activation tensor are multiplied to generate a respective compressed activation tensor, a respective pre-computed weight matrix and the respective compressed activation tensor are multiplied and, when appropriate, further applies an activation function to generate an output tensor that is provided as an activation tensor to a next layer. Inferencing proceeds iteratively through the layers of the retrained compressed LLM model until a last layer of the retrained compressed LLM model generates an output tensor that is provided as an output of the inferencing.

[0094] At least one technical advantage of the disclosed techniques relative to the prior art is that the disclosed techniques perform compression on the activation tensors of a machine learning model. Activation tensors are known to exhibit many redundancies. Accordingly, the disclosed techniques provide better opportunities for dimensionality reduction. In addition, the compression operations enabled by the disclosed techniques can be executed on any processor and do not need specialized hardware. Further, the disclosed techniques do not need any optimizations at run time, thereby facilitating overall execution efficiency. In addition, the disclosed techniques reduce the computational cost of inferencing using a machine learning model. These technical advantages represent one or more technological improvements over prior art approaches.

[0095] 1. In some embodiments, a computer-implemented method for compressing machine learning models comprises executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model, for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model, identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models, generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix, and generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

[0096] 2. The computer-implemented method of clause 1, wherein identifying the first projection matrix comprises determining that the corresponding partially compressed machine learning model generated using the first projection matrix has a highest evaluated performance relative to every other corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models.

[0097] 3. The computer-implemented method of clauses 1 or 2, further comprising, for the first activation tensor, computing a corresponding pre-computed weight matrix by multiplying the first projection matrix and the retrained corresponding weight matrix.

[0098] 4. The computer-implemented method of any of clauses 1-3, further comprising storing the first projection matrix and the corresponding pre-computed weight matrix in a data store.

[0099] 5. The computer-implemented method of any of clauses 1-4, wherein the trained machine learning model comprises a trained large language model.

[0100] 6. The computer-implemented method of any of clauses 1-5, wherein generating the corresponding partially compressed machine learning model for each pairing of the first activation tensor and a different fidelity metric included in the plurality of fidelity metrics comprises multiplying a corresponding projection matrix and the first activation tensor to generate a compressed first activation tensor and multiplying a corresponding weight matrix and the compressed first activation tensor.

[0101] 7. The computer-implemented method of any of clauses 1-6, further comprising generating the corresponding projection matrix using a plurality of eigenvectors derived from a corresponding estimated autocorrelation matrix.

[0102] 8. The computer-implemented method of any of clauses 1-7, wherein each eigenvector included in the plurality of eigenvectors comprises a different column of the corresponding projection matrix.

[0103] 9. The computer-implemented method of any of clauses 1-8, further comprising generating the corresponding estimated autocorrelation matrix by averaging a plurality of corresponding autocorrelation matrices.

[0104] 10. The computer-implemented method of any of clauses 1-9, wherein the different fidelity metrics comprise at least one of mean squared error (MSE), normalized MSE, general matrix multiplications output-referred MSE (GO-

MSE), network loss-referred MSE (NL-MSE), normalized GO-MSE, or normalized NL-MSE.

[0105] 11. In some embodiments, one or more non-transitory computer-readable media storing instruction that, when executed by one or more processors, cause the one or more processors to perform the steps of executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model, for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model, identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models, generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix, and generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

[0106] 12. The one or more non-transitory, computer-readable media of clause 11, wherein identifying the first projection matrix comprises determining that the corresponding partially compressed machine learning model generated using the first projection matrix has a highest evaluated performance relative to every other corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models.

[0107] 13. The one or more non-transitory, computer-readable media of clauses 11 or 12, wherein performance is evaluated by processing evaluation data via each corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models to generate inferencing results, and evaluating the inferencing results against at least one performance metric.

[0108] 14. The one or more non-transitory, computer-readable media of any of clauses 11-13, further comprising, for the first activation tensor, computing a corresponding pre-computed weight matrix by multiplying the first projection matrix and the retrained corresponding weight matrix.

[0109] 15. The one or more non-transitory, computer-readable media of any of clauses 11-14, wherein the trained machine learning model comprises a trained large language model.

[0110] 16. The one or more non-transitory, computer-readable media of any of clauses 11-15, wherein generating the corresponding partially compressed machine learning model for each pairing of the first activation tensor and a different fidelity metric included in the plurality of fidelity metrics comprises multiplying a corresponding projection matrix and the first activation tensor to generate a compressed first activation tensor and multiplying a corresponding weight matrix and the compressed first activation tensor.

[0111] 17. The one or more non-transitory, computer-readable media of any of clauses 11-16, further comprising generating the corresponding projection matrix using a plurality of eigenvectors derived from a corresponding estimated autocorrelation matrix.

[0112] 18. The one or more non-transitory, computer-readable media of any of clauses 11-17, further comprising generating the corresponding estimated autocorrelation matrix by averaging a plurality of corresponding autocorrelation matrices that are computed using different batches of training data.

[0113] 19. The one or more non-transitory, computer-readable media of any of clauses 11-18, wherein, during retraining, the corresponding weight matrix is modified to improve performance of the compressed machine learning model.

[0114] 20. In some embodiments, a system comprises one or more memories storing instructions, and one or more processors that are coupled to the one or more memories and, when executing the instructions, are configured to perform the steps of executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model, for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model, identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models, generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix, and generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

[0115] Any and all combinations of any of the claim elements recited in any of the claims and/or any elements described in this application, in any fashion, fall within the contemplated scope of the present disclosure and protection.

[0116] The descriptions of the various embodiments have been presented for purposes of illustration, but are not intended to be exhaustive or limited to the embodiments disclosed. Many modifications and variations will be apparent to those of ordinary skill in the art without departing from the scope and spirit of the described embodiments.

[0117] Aspects of the present embodiments may be embodied as a system, method or computer program product. Accordingly, aspects of the present disclosure may take the form of an entirely hardware embodiment, an entirely software embodiment (including firmware, resident software, micro-code, etc.) or an embodiment combining software and hardware aspects that may all generally be referred to herein as a "module" or "system." Furthermore, aspects of the present disclosure may take the form of a computer program product embodied in one or more computer readable medium(s) having computer readable program code embodied thereon.

[0118] Any combination of one or more computer readable medium(s) may be utilized. The computer readable medium may be a computer readable signal medium or a computer readable storage medium. A computer readable storage medium may be, for example, but not limited to, an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any suitable combination of the foregoing. More specific examples (a non-exhaustive list) of the computer readable storage medium would include the following: an electrical connection having one or more wires, a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), an optical fiber, a portable compact disc read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of the foregoing. In the context of this document, a computer readable storage medium may be any tangible medium that can contain, or store a program for use by or in connection with an instruction execution system, apparatus, or device.

[0119] Aspects of the present disclosure are described above with reference to flowchart illustrations and/or block diagrams of methods, apparatus (systems) and computer program products according to embodiments of the disclosure. It will be understood that each block of the flowchart illustrations and/or block diagrams, and combinations of blocks in the flowchart illustrations and/or block diagrams, can be implemented by computer program instructions. These computer program instructions may be provided to a processor of a general purpose computer, special purpose computer, or other programmable data processing apparatus to produce a machine. The instructions, when executed via the processor of the computer or other programmable data processing apparatus, enable the implementation of the functions/acts specified in the flowchart and/or block diagram block or blocks. Such processors may be, without limitation, general-purpose processors, special-purpose processors, application-specific processors, or field-programmable gate arrays.

[0120] The flowchart and block diagrams in the figures illustrate the architecture, functionality, and operation of possible implementations of systems, methods and computer program products according to various embodiments of the present disclosure. In this regard, each block in the flowchart or block diagrams may represent a module, segment, or portion of code, which comprises one or more executable instructions for implementing the specified logical function (s). It should also be noted that, in some alternative implementations, the functions noted in the block may occur out of the order noted in the figures. For example, two blocks shown in succession may, in fact, be executed substantially concurrently, or the blocks may sometimes be executed in the reverse order, depending upon the functionality involved. It will also be noted that each block of the block diagrams and/or flowchart illustration, and combinations of blocks in the block diagrams and/or flowchart illustration, can be implemented by special purpose hardware-based systems that perform the specified functions or acts, or combinations of special purpose hardware and computer instructions.

[0121] While the preceding is directed to embodiments of the present disclosure, other and further embodiments of the disclosure may be devised without departing from the basic scope thereof, and the scope thereof is determined by the claims that follow.

What is claimed is:

1. A computer-implemented method for compressing machine learning models, the method comprising:

executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model;

for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model;

identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models;

generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix; and

generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

2. The computer-implemented method of claim **1**, wherein identifying the first projection matrix comprises determining that the corresponding partially compressed machine learning model generated using the first projection matrix has a highest evaluated performance relative to every other corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models.

3. The computer-implemented method of claim **1**, further comprising, for the first activation tensor, computing a corresponding pre-computed weight matrix by multiplying the first projection matrix and the retrained corresponding weight matrix.

4. The computer-implemented method of claim **3**, further comprising storing the first projection matrix and the corresponding pre-computed weight matrix in a data store.

5. The computer-implemented method of claim **1**, wherein the trained machine learning model comprises a trained large language model.

6. The computer-implemented method of claim **1**, wherein generating the corresponding partially compressed machine learning model for each pairing of the first activation tensor and a different fidelity metric included in the plurality of fidelity metrics comprises multiplying a corresponding projection matrix and the first activation tensor to generate a compressed first activation tensor and multiplying a corresponding weight matrix and the compressed first activation tensor.

7. The computer-implemented method of claim **6**, further comprising generating the corresponding projection matrix using a plurality of eigenvectors derived from a corresponding estimated autocorrelation matrix.

8. The computer-implemented method of claim **7**, wherein each eigenvector included in the plurality of eigenvectors comprises a different column of the corresponding projection matrix.

9. The computer-implemented method of claim **7**, further comprising generating the corresponding estimated autocorrelation matrix by averaging a plurality of corresponding autocorrelation matrices.

10. The computer-implemented method of claim **1**, wherein the different fidelity metrics comprise at least one of mean squared error (MSE), normalized MSE, general matrix multiplications output-referred MSE (GO-MSE), network loss-referred MSE (NL-MSE), normalized GO-MSE, or normalized NL-MSE.

11. One or more non-transitory computer-readable media storing instruction that, when executed by one or more processors, cause the one or more processors to perform the steps of:

executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model;

for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model;

identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models;

generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix; and

generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

12. The one or more non-transitory, computer-readable media of claim **11**, wherein identifying the first projection matrix comprises determining that the corresponding partially compressed machine learning model generated using the first projection matrix has a highest evaluated performance relative to every other corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models.

13. The one or more non-transitory, computer-readable media of claim **12**, wherein performance is evaluated by processing evaluation data via each corresponding partially compressed machine learning model included in the plurality of corresponding partially compressed machine learning models to generate inferencing results, and evaluating the inferencing results against at least one performance metric.

14. The one or more non-transitory, computer-readable media of claim **11**, further comprising, for the first activation tensor, computing a corresponding pre-computed weight matrix by multiplying the first projection matrix and the retrained corresponding weight matrix.

15. The one or more non-transitory, computer-readable media of claim **11**, wherein the trained machine learning model comprises a trained large language model.

16. The one or more non-transitory, computer-readable media of claim **11**, wherein generating the corresponding partially compressed machine learning model for each pairing of the first activation tensor and a different fidelity metric included in the plurality of fidelity metrics comprises multiplying a corresponding projection matrix and the first activation tensor to generate a compressed first activation tensor and multiplying a corresponding weight matrix and the compressed first activation tensor.

17. The one or more non-transitory, computer-readable media of claim **16**, further comprising generating the corresponding projection matrix using a plurality of eigenvectors derived from a corresponding estimated autocorrelation matrix.

18. The one or more non-transitory, computer-readable media of claim **17**, further comprising generating the corresponding estimated autocorrelation matrix by averaging a plurality of corresponding autocorrelation matrices that are computed using different batches of training data.

19. The one or more non-transitory, computer-readable media of claim **11**, wherein, during retraining, the corresponding weight matrix is modified to improve performance of the compressed machine learning model.

20. A system, comprising:

one or more memories storing instructions; and

one or more processors that are coupled to the one or more memories and, when executing the instructions, are configured to perform the steps of:

executing a first trained machine learning model on training data to identify one or more activation tensors associated with at least one layer of the trained machine learning model;

for each pairing of a first activation tensor included in the one or more activation tensors and a different fidelity metric included in a plurality of fidelity metrics, generating a corresponding partially compressed machine learning model;

identifying a first projection matrix corresponding to the first activation tensor based on the plurality of corresponding partially compressed machine learning models;

generating a compressed machine learning model by at least multiplying the first projection matrix and a corresponding weight matrix; and

generating a retrained compressed machine learning model by at least retraining the corresponding weight matrix while keeping the first projection matrix static.

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