Review Notes on Quantum LLMs

Quantum Methods Capable of Enhancing LLMs

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Definition

A language model architecture that integrates **quantum computing components** with classical LLMs.

Motivation for QLLMs

- Potential quantum speedup effects
- Advantages over classical algorithms **in certain tasks**
  - Quantum system simulation in chemistry;
  - RSA-related computational problems;
  - Language-related applications.

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Quantum-Inspired Techniques in LLMs

Quantum NLP: Model Families Overview

Reference: Varmantchaonala et al.(2024)[3]

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- **Quantum Bag-of-Words**: quantum-probabilistic representations ignoring word order; efficient but limited.
- **Tensor Product Representations (TPR)**:
  - Positional TPR
  - Contextual TPR
  - Fock-space models: integrate positional and contextual information using harmony operators.
- **Word2Ket / Word2KetXS**

QBoWs and TPRs I

Quantum Bag-of-Words (QBoW) extends classical Bag-of-Words by encoding a document as a quantum state:

$$|d\rangle = \sum_i \delta_i |w_i\rangle, \qquad D = |d\rangle\langle d|.$$

The density matrix D captures term correlations through off-diagonal entries. QBoW is simple and enables quantum measurementbased document classification, but it ignores word order and syntactic structure.

Tensor Product Representations (TPR) aim to encode linguistic structure using tensor products.

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QBoWs and TPRs II

- **Positional TPR (pTPR)**: bind word and its syntactic position:

$$s_i \otimes n_i.$$

This accurately reflects grammar but leads to rapid dimensional growth.

- **Contextual TPR (cTPR)**: bind a word with its contextual window:

$$|w_{i-1}\rangle \otimes |w_i\rangle \otimes |w_{i+1}\rangle.$$

This reduces structural mixing and controls tensor size, though it still increases dimensionality and cannot fully reflect long-range dependencies.

Word2Ket & Word2KetXS

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(1) Word2Ket

- Decompose high-dim vector $|\mathbf{v}\rangle$ into tensor product of low-dim vectors:

$$|\mathbf{v}\rangle = \sum_{j=1}^{r} \bigotimes_{i=1}^{n} v'_{ij}$$

---

(2) Word2KetXS: Full Vocabulary Compression

- Extend Word2Ket to compress the entire sparse vocabulary matrix **M**:

$$\mathbf{M} = \sum_{j=1}^{r} \bigotimes_{i=1}^{n} \mathbf{M}'_{ij}$$

Chronological tree of QNLP models

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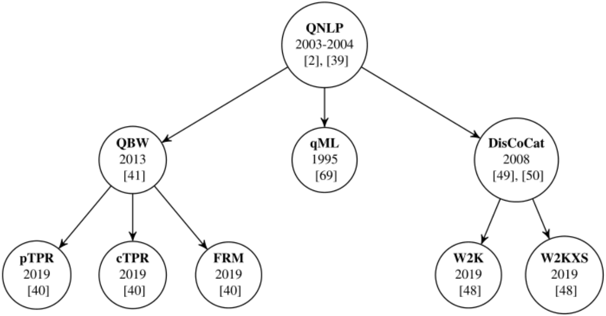

FIGURE 2. Chronological tree of QNLP models. qML stands for quantum machine learning.

Example of QLM

Reference: Basile et al.(2017)[4]

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For a sequence $w = (w_1, \ldots, w_n)$, encode as $w \mapsto |w\rangle$.
Let $\Pi_w := |w\rangle\langle w|$ and define conditional steps:

$$\text{Init:} \quad P(w_1; \rho_0, U) = \mathrm{Tr}(\rho_0 \Pi_{w_1}),$$

$$\text{Projection:} \quad \rho_1' = \frac{\Pi_{w_1} \rho_0 \Pi_{w_1}}{\mathrm{Tr}(\Pi_{w_1} \rho_0 \Pi_{w_1})},$$

$$\text{Evolution:} \quad \rho_1 = U \rho_1' U^\dagger.$$

Termination:

$$P(w \mid \rho_0, U) = P(w_1; \rho_0, U) \prod_{i=2}^{n} P(w_i \mid w_{1,\cdots,i-1}; \rho_0, U).$$

Memory via entanglement

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- Perplexity (to be minimised):

$$\Gamma(\rho_0, U) = \exp\left(-\frac{1}{C}\sum_{w\in S}\log P(w \mid \rho_0, U)\right).$$

Ancillary system

$$\mathcal{H}_2 = \mathcal{H}_{\mathrm{anc}} \otimes \mathcal{H}.$$

Projectors lift to $\Pi_w^{(2)} = I_D \otimes \Pi_w$.

Learning the unitary operator

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Quantum embedding via low-dimensional vectors. With idea following word2vec and GloVe, each word w is mapped through a fixed embedding:

$$w \mapsto (\alpha_1(w), \alpha_2(w), \ldots, \alpha_p(w)).$$

Learning a small set of base unitaries. The model learns only p base unitaries:

$$\{U_1, U_2, \ldots, U_p\}, \qquad U_i \in \mathbb{C}^{DN \times DN}.$$

Strengths and Limitations

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Strengths

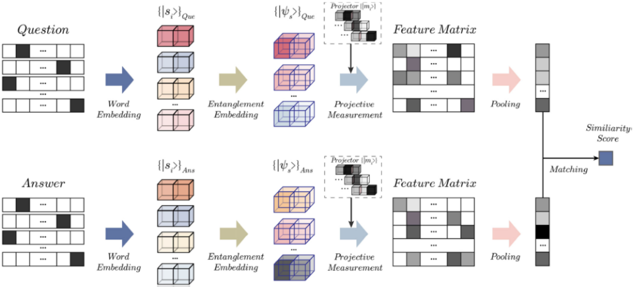
- Interference & entanglement $\rightarrow$ sequence-level correlations
- Compact trace formula for $P(w)$
- Fast inference once unitaries are precomputed

Limitations

- Scalability: DN grows with vocabulary size
- Current model works only for small vocabularies
- Training is computationally intensive (unitarity constraints + many parameters)

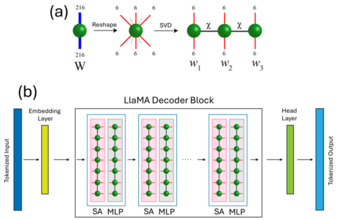
QLM-EE

Reference: Chen et al.(2021)[5]



CompactifAI

Reference: Tomut et al.(2024)[6], Vaswani et al.(2017)[7]



Weight Matrices in Transformer Layers

Self-Attention Linear Projections

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V.$$

Attention Output: $O = \mathrm{Attention}(Q, K, V)\, W_O.$
Feed-Forward Network

$$H = \sigma(XW_1 + b_1), \quad Y = HW_2 + b_2.$$

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Conceptual parallel (MPS)

$$|\psi\rangle = \sum_{i_1, i_2, \ldots, i_N} A^{[1]}_{i_1} A^{[2]}_{i_2} \cdots A^{[N]}_{i_N} \, |i_1 i_2 \cdots i_N\rangle.$$

Matrix Product Operator, MPO

$$W_{i_1 \cdots i_L,\, j_1 \cdots j_L} = \sum_{\alpha_1, \ldots, \alpha_{L-1}} G^{(1)}_{i_1 j_1,\, \alpha_1} \, G^{(2)}_{i_2 j_2,\, \alpha_1 \alpha_2} \cdots G^{(L)}_{i_L j_L,\, \alpha_{L-1}}.$$

- The bond dimension χ: the compression ratio.

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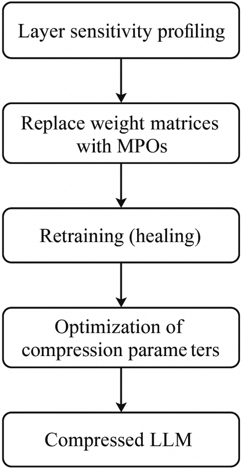

Experiment results

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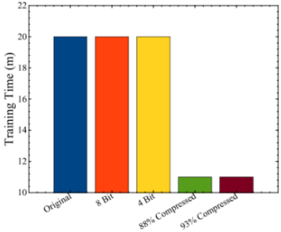
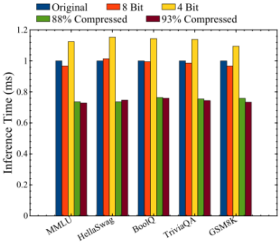
- 93% memory reduction; 70% parameter reduction
- approximately 25% faster inference; around 50% faster training
- a 2 - 3 % drop in accuracy





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QLLM via Tensor Network Disentanglers

Reference: Aizpurua et al.(2024)[8]

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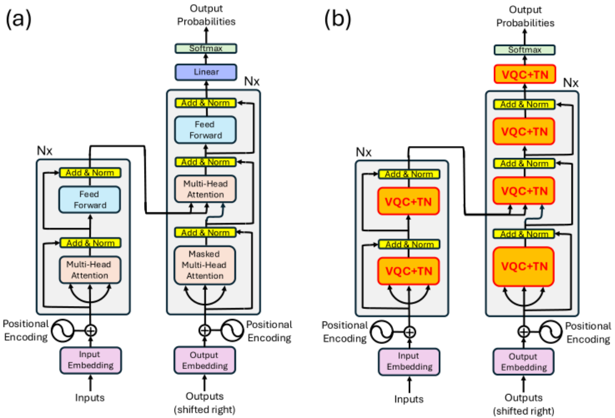
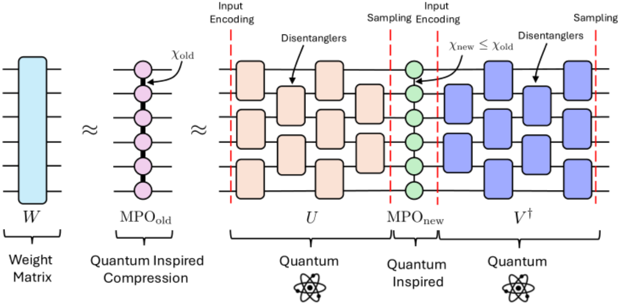


Quantum Disentanglers

- $M = U_{\text{left}}^{\dagger} M_{\text{new}} U_{\text{right}}$.



Key Experimental Observations

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Observations

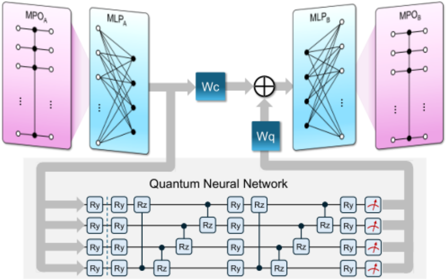
- Required bond dimension: **significantly reduced** $\Longrightarrow$ Quantum circuit effectively captures higher-order correlations.
- For the **same bond dimension**, the quantum-assisted MPO yields a **substantially lower reconstruction error**.
- Performance: remains very close to the original model.

Quantum enhanced fine tuning

Reference: Kong et al.(2025)[9]

Quantum Tensor Hybrid Adaptation,QTHA

- A parameter-efficient fine-tuning (PEFT) method;
- Dynamically adjusts feature weights through parameter tuning and outputs a combination of features from MPO and QNN.



State Revolution in QNN

$$|\Psi(x)\rangle = \bigotimes_{i=1}^{r} R_Z(x_i)\,|0\rangle,$$

$$|\phi(x)\rangle = U(\theta)|\psi(x)\rangle = \prod_{l=1}^{L}\left(\bigotimes_{i=1}^{q} RY(\theta_{l,i}) \cdot \mathrm{CZ}(\theta_{l,i,j})\right),$$

Expectation values

$$y_i = \langle\phi(x)|Z_i|\phi(x)\rangle \in [-1,1].$$

Main Contributions

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- First implementation of quantum computing inference for LLM on **quantum hardware**;
- Significant reduction in trainable parameters (**76**% compared to LoRA);
- Enhancing the performance of LLM fine-tuning.

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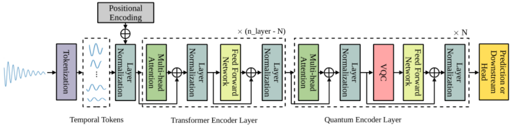
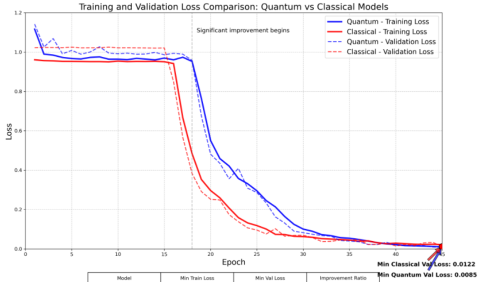
Quantum Enhanced Self Attention

Reference: Chen et al.(2025)[10]





Model	Min Train Loss	Min Val Loss	Improvement Ratio
Quantum	0.0106	0.0085	105.73
Classical	0.0219	0.0122	43.94

Key Observations:
1. Both models show similar training patterns but different convergence rates
2. The quantum model achieves lower final training and validation loss
3. The classical model shows more validation loss fluctuation after epoch 30

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DisCoCat Framework

- **Complex Types**: Constructed via left cancellation n^l and right cancellation n^r. For example:
  - Adjectives: with type $n \cdot n^l$.
  - Transitive verbs: with type $n^r \cdot s \cdot n^l$.
- **Syntactic Parsing**

$$\text{Cats}(n) \qquad \text{eat}(n^r \cdot s \cdot n^l) \qquad \text{fish}(n)$$

$$\mathrm{Meaning}(\mathit{sentence}) = \epsilon_N \otimes 1_S \otimes \epsilon_N(\overrightarrow{\mathrm{Cats}} \otimes \overrightarrow{\mathrm{eat}} \otimes \overrightarrow{\mathrm{fish}})$$

Syntactic structure $\Longrightarrow$ Tensor network structure $\Longrightarrow$ Quantum circuit structure

Quantum-Native Self Attention I

Reference: Shi et al.(2025)[12]

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$$x_i \longmapsto |x_i\rangle \xrightarrow{U_{\text{att}}} |\mathrm{Att}(x_i)\rangle$$

1. **Quantum Embedding**

$$x_i \in \mathbb{R}^d \;\mapsto\; |x_i\rangle \in \mathbb{C}^{2^n}$$

2. **Quantum Key–Query Inner Product**

$$q_i k_j^\top$$

SWAP-test / Hadamard-test / parameterized circuits:

$$\mathrm{sim}(i,j) = \langle q_i | k_j \rangle$$

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3. **Quantum Attention Weighting** Parameterized controlled rotation:

$$\mathrm{softmax}(s_{ij}) \approx f_\theta(s_{ij})$$

Final attention state:

$$|\mathrm{Att}(x_i)\rangle \propto \sum_j f_\theta(s_{ij}) \, |v_j\rangle$$

Quantum-Native Self Attention III

Reference: Shi et al.(2025)[12]

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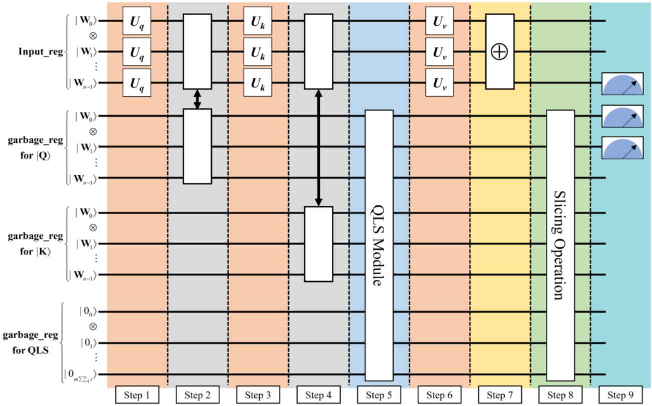

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Future Outlook

Reference: Pan et al.(2025)[13]

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Based on AQCF Framework (Bridging Classical and Quantum Computing)

- Gradual transition: Classical LLM $\rightarrow$ Hybrid Q-Enhanced $\rightarrow$ Quantum-Native
- Principles: progressive, scalable, hardware-feasible
- Focus: shallow quantum modules; adaptive circuits; noise-aware design

Potential Strategic Directions

- Scalable quantum text processing for NISQ
- Quantum-enhanced attention
- Quantum memory and semantic retrieval

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Thank You!