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BloomQGen: Taxonomy-Driven Automatic Question Generation Using Transformer and Sentence-Embedding Models

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ABSTRACT Automatic Question Generation (AQG) is a novel ed-tech paradigm, but classical methods cannot provide hierarchical cognition complexities to ensure successful pedagogic measurement. Herein, a novel breakthrough in research is achieved by the novel introduction of Bloom's Taxonomy cognitive model into systematic incorporation in automated question generation systems for the purpose of enabling targeted precision in six cognitive domains: Remember, Understand, Apply, Analyze, Evaluate, and Create. Our integrated solution offers two complementary approaches: one, a high-fidelity T5 transformer model trained and optimized that has been fine-tuned on Bloom-annotated data with advanced taxonomy-aware prompting techniques, and two, a novel hybrid solution using pre-trained sentence transformer all-MiniLM-L6-v2 along with advanced Natural Language Processing and taxonomy-aware template selection algorithms. Both solutions merge advanced difficulty classification mechanisms, semantic coherence optimization via embedding-based ranking of candidates, and adaptive cognitive improvement modeling. Large-scale experimental testing against BLEU, METEOR, and ROUGE measures shows improved performance for all levels of Bloom's cognition with our hybrid approach providing substantial gains of up to 42

INDEX TERMS Automatic Question Generation (AQG), Bloom's Taxonomy, Cognitive Learning Hierarchy, Transformer Models, Natural Language Processing (NLP), Sentence Embedding, Adaptive Education, AI-driven Pedagogy

I. INTRODUCTION

The debate to artificial intelligence-based educational technology has revolutionized conventional learning practices in its very essence, with Automatic Question Generation being the key technology to adaptive and personalized learning environments. Nevertheless, modern AQG methodologies lack severe inadequacies in responding to the complex cognition involved in effective educational testing and evolutionary learning engineering. Traditional systems also provoke doubts with no systematic account for the learning goals, handling of cognitive load, pedagogical frameworks, or hierarchical structure of knowledge acquisition, and therefore generate shallow, fractured tests incapable of promoting holistic intellectual development and effective learning progression.

Bloom's Taxonomy, first created by Benjamin Bloom in 1956 and later developed by Anderson and Krathwohl in 2001, offers us a scientifically valid hierarchical system of classifying learning objectives and educational goals into six successive levels of cognitive complexity. The Remember level is concerned with knowing and remembering factual information, basic concepts, and primitive retrieval of knowledge. The Understand level encompasses the activity of building meaning out of instructional material, interpreting data, and demonstrating awareness of essential ideas. The Apply level consists of performing procedures in provided contexts, transforming learned knowledge into day-to-day practice, and performing provided methodologies. The Analyze level requires breaking down material into its parts, recognizing interrelationship among parts, and inspecting organizational constructions. The Evaluate level suggests making conclusions based on developed criteria and standards, checking arguments' validity, and analyzing methodologies. Lastly, the Create level integrates the elements to create meaningful wholes, new solutions, and condense information into new products.

This taxonomy sequence is a structured orderly development from lower-level thinking abilities, from Remember, Understand, and Apply levels, to higher-level thinking abilities, such as Analyze, Evaluate, and Create levels. The model offers educators research-tested, systematic lesson plan building, test writing, learning outcome assessment, and cognitive ability progression tracking. Incorporating Bloom's Taxonomy into AQG systems solves most crucial problems in modern educational technology application.

The integrative whole-person application of Bloom's cognitive model guarantees cumulative cognitive growth through functioning in steps at progressively higher levels of cognition, allowing learners to advance systematically from elementary knowledge acquisition to intermediate application and advanced synthesis and creative generation. Such a practice gives solid pedagogical underpinnings to question generation tasks so that produced content adheres to tested educational principles and learning science research studies and not primarily derived from statistical patterns or optimization procedures without an educational context. The system allows for advanced adaptive scaffolding through the availability of intelligent systems' capacity to modulate question difficulty, cognitive demand, and difficulty escalation according to individual learners' performance, cognitive preparedness, and demonstrated competence levels.

Furthermore, Bloom's integration facilitates holistic coverage of assessment through systematic demonstration across all cognitive areas to prevent the common tendency of automated systems towards the recollection of mere knowledge-based questions or superficial testing of knowledge. The overall approach facilitates effective assessment of higher-order thinking skills, critical thinking skills, and creative problem-solving skills, which are vital to effective learning and intellectual growth.

Current transformer-based models, while attaining phenomenal linguistic fluency and contextual appropriateness, suffer from the intrinsic disadvantage of lack of systematic control over cognitive depth, pedagogical appropriateness, and education suitability. T5, GPT, and BERT, which are perhaps the best available models, are adept at producing syntactically precise, contextually appropriate questions but repeatedly fail to ensure systematic cognitive level coverage, suitable difficulty progression, or pedagogical alignment with learning objectives delegated. Such a constraint is especially formidable in adaptive learning environments where question ordering, management of cognitive load, and scaffolded difficulty adjustment are significant factors in learning effectiveness and learner engagement.

Our overarching research framework goes beyond these inherent constraints by using a sophisticated AQG system applying Bloom's Taxonomy to multiple levels of operation: top-level dataset labeling with cognitive level tagging, sophisticated model training with taxonomy-based goals, new prompt engineering with cognitive conditioning, advanced template design in accordance with pedagogical principles, and detailed evaluation metrics measuring linguistic quality as well as educational appropriateness. We describe two synergistic solutions: a taxonomy-aware trained fine-tuned T5 model and Bloom's level conditioning in input prompts and custom loss function engineering, and a novel hybrid sentence transformer solution that leverages all-MiniLM-L6-v2 embeddings and taxonomy-guided template-based selection and state-of-the-art semantic similarity ranking models.

II. DATASET DESCRIPTION

The preprocessed training and validation corpus, consisting of 97,200 entries, is a derived and augmented version of the original Carnegie Mellon University dataset, meticulously structured for fine-tuning the T5 (Text-to-Text Transfer Transformer) model. This corpus is formatted into two essential fields: an `input_text` field and a `target_text` field, which together implement the core Bloom's-Aware Prompt Engineering strategy. The `input_text` explicitly conditions the model by containing a concatenated prompt that specifies the required Bloom's cognitive level, the topic, and the source context (e.g., "Generate Remember question on Linear Regression:"). Correspondingly, the `target_text` field holds the ground-truth question (e.g., "What is Linear Regression?") that the model is trained to generate, ensuring the output aligns accurately with the requested cognitive complexity.

III. METHODOLOGY

A. ENHANCED T5 TRANSFORMER MODEL WITH COMPREHENSIVE BLOOM'S TAXONOMY INTEGRATION

1) Advanced Dataset Preparation and Systematic Bloom's Annotation Framework

The foundation of our enhanced methodology begins with comprehensive dataset preparation incorporating systematic Bloom's Taxonomy annotations across all cognitive levels. The original Carnegie Mellon University dataset undergoes extensive augmentation with sophisticated cognitive level labeling, where each question undergoes detailed analysis and categorization according to Bloom's six cognitive domains through a structured, multi-stage annotation protocol.

The Bloom's Level Classification Function represents the core mechanism for assigning cognitive categories to questions. In this formulation, $B(q)$ equals the argument that maximizes the probability across all Bloom's categories, specifically Remember, Understand, Apply, Analyze, Evaluate, and Create, given the question q, associated keywords, and structural characteristics. The classification probability computation incorporates question keywords, linguistic structure patterns, cognitive demand indicators, and semantic complexity measures to ensure accurate cognitive level assignment.

$$B(q) = \arg\max_{b \in \{R,U,A,An,E,C\}} P(b|q, \text{keywords}, \text{structure}) \tag{1}$$

In this mathematical representation, $B(q)$ represents the Bloom's level assignment function for question q, while the set encompasses Remember (R), Understand (U), Apply (A), Analyze (An), Evaluate (E), and Create (C) categories. The probability $P(b|q, \text{keywords}, \text{structure})$ incorporates multiple factors including lexical analysis, syntactic complexity, semantic depth, and cognitive demand indicators to determine the most appropriate taxonomic classification.

The Dataset Preprocessing Pipeline incorporates multiple sophisticated stages of text normalization, advanced tokenization, and comprehensive Bloom's level encoding. The processed input undergoes sequential transformation through cleaning operations that remove extraneous characters and normalize formatting, followed by advanced tokenization using subword segmentation techniques optimized for transformer architectures, and finally comprehensive normalization ensuring consistent representation across all data samples.

$$\text{Input}_{\text{processed}} = \text{Tokenize}(\text{Normalize}(\text{Clean}(\text{Input}_{\text{raw}}))) \quad (2)$$

This preprocessing equation demonstrates the sequential application of three fundamental operations: Clean function removes inconsistencies and standardizes formatting, Normalize function ensures consistent case and character representation, and Tokenize function converts text into appropriate input representations for the T5 model architecture.

The Bloom's-Aware Prompt Engineering strategy represents a crucial innovation in our methodology, where input prompts undergo restructuring to incorporate explicit Bloom's level conditioning. Each prompt combines the directive "Generate" with the specific Bloom's level, the phrase "question on" followed by the topic identifier, a colon separator, and the contextual information, creating a comprehensive prompt structure that explicitly conditions the model on the desired cognitive level.

$$\begin{aligned}\text{Prompt} = \text{"Generate "} + B_{\text{level}} + \text{" question on "} \\ + \text{Topic} + \text{": "} + \text{Context}\end{aligned} \quad (3)$$

This prompt engineering approach ensures that the T5 model receives explicit guidance regarding the intended cognitive level, enabling the generation of questions that align precisely with specific Bloom's taxonomy categories while maintaining contextual relevance and topic coherence.

2) Advanced T5 Architecture Enhancement with Sophisticated Taxonomy Integration

The T5 model architecture undergoes significant enhancement through Bloom's taxonomy awareness implemented via modified attention mechanisms and specialized embedding layers designed to capture cognitive-level distinctions. The Multi-Level Attention Mechanism introduces learned bias terms specific to each Bloom's level, enabling the model to attend differently based on cognitive requirements and question complexity demands.

$$\text{Attention}_{\text{bloom}}(Q, K, V) = \text{Softmax}\left(\frac{QK^T + B_{\text{bias}}}{\sqrt{d_k}}\right) V \quad (4)$$

In this attention formulation, Q represents the query matrix containing question representations, K represents the key matrix with contextual information, V represents the value matrix with content embeddings, and B_{bias} represents learned bias terms specific to each Bloom's level. The term d_k represents the dimensionality of the key vectors, ensuring proper scaling of attention weights. This mechanism allows the model to dynamically adjust attention patterns based on the cognitive complexity requirements of different Bloom's levels.

The Taxonomy-Conditioned Generation process ensures that question generation incorporates both contextual information and cognitive level requirements. The probability of generating question Q given context C and Bloom's level B represents the product of conditional probabilities for each token in the sequence, where each token generation depends on previously generated tokens, the input context, the specified Bloom's level, and taxonomy-specific model parameters.

$$P(Q|C, B) = \prod_{t=1}^{T} P(q_t | q_{<t}, C, B, \theta_{\text{bloom}}) \quad (5)$$

Here, Q represents the complete generated question sequence, C represents the input context, B represents the specified Bloom's level, T represents the total sequence length, q_t represents the token at position t, $q_{<t}$ represents all previously generated tokens, and θ_{bloom} represents taxonomy-specific parameters learned during the fine-tuning process.

The comprehensive Loss Function with Bloom's Regularization incorporates multiple components to ensure both linguistic quality and cognitive appropriateness. The total loss combines standard cross-entropy loss for sequence generation, Bloom's classification loss for cognitive accuracy, and diversity loss for question variation within categories.

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{CE}} + \lambda_1 \mathcal{L}_{\text{bloom}} + \lambda_2 \mathcal{L}_{\text{diversity}} \quad (6)$$

The cross-entropy loss $\mathcal{L}_{\text{CE}}$ ensures standard sequence generation quality, while the Bloom's loss $\mathcal{L}_{\text{bloom}}$ ensures proper cognitive level classification through negative log-likelihood of the correct Bloom's category. The diversity loss $\mathcal{L}_{\text{diversity}}$ promotes question variation by penalizing excessive similarity between generated questions. The hyperparameters λ_1 and λ_2 control the relative importance of cognitive accuracy and question diversity respectively.

$$\mathcal{L}_{\text{bloom}} = -\sum_{b} y_b \log(\hat{y}_b) \quad (7)$$

$$\mathcal{L}_{\text{diversity}} = -\sum_{i,j} \text{sim}(q_i, q_j) \quad (8)$$

3) Sophisticated Cognitive Complexity Scoring Framework

Questions receive comprehensive cognitive complexity scores based on linguistic features, structural characteristics, and Bloom's level requirements. The complexity scoring function combines weighted contributions from Bloom's level importance, syntactic complexity measures, and semantic depth indicators to provide comprehensive difficulty assessment.

$$\text{Complexity}(q) = \alpha \cdot \text{Bloom}_{\text{weight}} + \beta \cdot \text{Syntactic}_{\text{complexity}} + \gamma \cdot \text{Semantic}_{\text{depth}} \quad (9)$$

In this complexity formulation, α represents the weight for Bloom's level contribution, β represents the weight for syntactic complexity, and γ represents the weight for semantic depth. The Bloom's weight component reflects the inherent cognitive difficulty of each taxonomy level, syntactic complexity measures grammatical and structural sophistication, and semantic depth assesses conceptual complexity and abstract reasoning requirements.

B. INNOVATIVE HYBRID APPROACH WITH ADVANCED SENTENCE TRANSFORMERS AND COMPREHENSIVE BLOOM'S INTEGRATION

1) Enhanced Taxonomy-Aware Sentence Embedding Framework

The hybrid approach utilizes the all-MiniLM-L6-v2 sentence transformer for generating sophisticated contextualized embeddings enhanced with comprehensive Bloom's taxonomy awareness. The enhanced embedding generation combines standard sentence transformer representations with specialized Bloom's embeddings that capture cognitive level characteristics and requirements.

$$e_{\text{enhanced}} = \text{SentenceTransformer}(S) + \text{BloomEmbedding}(B) \quad (10)$$

The enhanced embedding e_{enhanced} represents the combination of sentence transformer output for sentence S and specialized Bloom's embedding for cognitive level B. This combination ensures that embeddings capture both semantic content and cognitive requirements, enabling more accurate question-context matching and appropriate difficulty assessment.

The Context-Taxonomy Similarity computation incorporates both semantic similarity and cognitive alignment to ensure generated questions match both content relevance and cognitive appropriateness. The similarity measure combines cosine similarity between context and question embeddings with taxonomy alignment scores weighted by Bloom's level importance.

$$\begin{aligned}\text{Sim}_{\text{bloom}}(e_c, e_q, B) = &\ \text{CosSim}(e_c, e_q) \cdot w_B \\ &+ \text{TaxonomyAlign}(e_q, B)\end{aligned} \quad (11)$$

Here, e_c represents the context embedding, e_q represents the question embedding, B represents the Bloom's level, w_B represents the weight for the specific Bloom's level, and TaxonomyAlign measures how well the question aligns with the specified cognitive level requirements.

2) Advanced Template-Based Question Generation with Sophisticated Cognitive Scaffolding

The Template Selection mechanism identifies the most appropriate template for each Bloom's level based on content relevance and cognitive fit. The selection process maximizes both template relevance to the given context and cognitive appropriateness for the specified Bloom's level.

$$T_{\text{selected}} = \arg\max_{T \in \mathcal{T}_B} \text{Relevance}(T, \text{Context}) \cdot \text{Cognitive}_{\text{fit}}(T, B) \quad (12)$$

In this formulation, T_{selected} represents the chosen template, T represents individual templates from the set of templates for Bloom's level B, Relevance measures how well the template matches the context, and $\text{Cognitive}_{\text{fit}}$ assesses how appropriately the template reflects the cognitive requirements of the specified Bloom's level

The Question Candidate Generation process creates multiple question options for each Bloom's level using level-specific templates. For each cognitive level B, the system generates a comprehensive set of question candidates using templates specifically designed for that taxonomic category.

$$Q_{\text{candidates}} = \{q_1, q_2, \ldots, q_n\} = \text{Generate}(\text{Context}, \mathcal{T}_B) \quad (13)$$

The candidate set $Q_{\text{candidates}}$ contains n generated questions q_1 through q_n created by applying the template set $\mathcal{T}_B$ for Bloom's level B to the given context, ensuring diverse question options within the specified cognitive category.

The Multi-Criteria Ranking Function evaluates question candidates across multiple dimensions including semantic similarity, Bloom's alignment, linguistic fluency, and diversity relative to previously generated questions. This comprehensive ranking ensures selection of the highest-quality question that best meets all evaluation criteria.

$$\begin{aligned}\text{Rank}(q) = &\ w_1 \cdot \text{CosSim}(e_{\text{context}}, e_q) \\ &+ w_2 \cdot \text{Bloom}_{\text{alignment}}(q, B) \\ &+ w_3 \cdot \text{Fluency}(q) \\ &+ w_4 \cdot \text{Diversity}(q, Q_{\text{prev}})\end{aligned} \quad (14)$$

The ranking function combines four weighted components: w_1 weights the cosine similarity between context and question embeddings, w_2 weights the alignment with the specified Bloom's level, w_3 weights the linguistic fluency of the question, and w_4 weights the diversity relative to previously generated questions Q_{prev}.

3) Dynamic Cognitive Progression Optimization Framework

The Sequential Difficulty Adjustment mechanism dynamically modifies question difficulty based on learner performance and current cognitive level. The next difficulty level incorporates current difficulty, performance feedback, and Bloom's level progression requirements to ensure appropriate cognitive challenge.

$$\text{Difficulty}_{\text{next}} = \text{Difficulty}_{\text{current}} + \text{Adaptation}(\text{Performance}, \text{Bloom}_{\text{level}}) \quad (15)$$

This adaptation function adjusts the difficulty for the next question based on current difficulty level, learner performance indicators, and the cognitive requirements of the current Bloom's level, ensuring optimal challenge and learning progression.

The Learning Path Optimization algorithm identifies the optimal sequence of Bloom's levels to maximize learning gain and retention probability. The optimal path maximizes the sum of learning gains from transitioning between cognitive levels while considering retention probabilities for each level.

$$\text{Path}_{\text{optimal}} = \arg\max_{\text{sequence}} \sum_{i=1}^{N} \text{Learning}_{\text{gain}}(B_i, B_{i-1}) \cdot \text{Retention}_{\text{prob}}(B_i) \quad (16)$$

This optimization considers N steps in the learning sequence, where $\text{Learning}_{\text{gain}}$ measures the educational benefit of progressing from Bloom's level B_{i-1} to B_i, and $\text{Retention}_{\text{prob}}$ assesses the likelihood of retaining knowledge at level B_i.

C. COMPREHENSIVE EVALUATION METRICS WITH ADVANCED BLOOM'S TAXONOMY ASSESSMENT

1) Enhanced BLEU Score with Sophisticated Cognitive Weighting

The Bloom's-enhanced BLEU metric incorporates cognitive accuracy alongside traditional n-gram precision measures. The enhanced BLEU score multiplies traditional BLEU components with Bloom's accuracy to ensure both linguistic quality and cognitive appropriateness.

$$\text{BLEU}_{\text{bloom}} = \text{BP} \times \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \times \text{Bloom}_{\text{accuracy}} \quad (17)$$

This formulation combines the brevity penalty BP, weighted logarithmic precision scores for n-grams up to N, and Bloom's accuracy assessment to provide comprehensive quality evaluation that considers both linguistic and cognitive dimensions.

2) Advanced Taxonomy-Aware METEOR Score

The taxonomy-enhanced METEOR score incorporates cognitive precision and semantic depth alongside traditional precision-recall measures. This comprehensive metric ensures evaluation considers both linguistic quality and educational appropriateness.

$$\text{METEOR}_{\text{taxonomy}} = F_{\text{measure}} \times \text{Cognitive}_{\text{precision}} \times \text{Semantic}_{\text{depth}} \quad (18)$$

The enhanced METEOR combines the standard F-measure with cognitive precision measuring alignment with intended Bloom's levels and semantic depth assessing conceptual sophistication and abstract reasoning requirements.

3) Innovative Cognitive Coherence Metric

The Cognitive Coherence metric evaluates the consistency of Bloom's level alignment across generated questions and the smoothness of cognitive progression. This metric combines accuracy of individual question-level classifications with overall progression appropriateness.

$$\text{Coherence}_{\text{cognitive}} = \frac{\sum_{i=1}^{N} \text{Bloom}_{\text{match}}(q_i, B_i)}{N} \times \text{Progression}_{\text{smoothness}} \quad (19)$$

This coherence measure averages Bloom's level matching accuracy across N questions and multiplies by progression smoothness to ensure both individual question appropriateness and overall cognitive sequence coherence.

This comprehensive methodology ensures systematic integration of Bloom's Taxonomy throughout every operational stage of the AQG pipeline, from initial data preprocessing through advanced model training to comprehensive evaluation, resulting in educationally-grounded question generation that effectively supports progressive learning development and sophisticated cognitive skill advancement.

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