**Title: Accelerated Semantic Search with MAX Engine: A Case Study on Counterfactual Statement Classification**

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**Abstract:**

This paper explores the application of MAX Engine, an inference-optimized engine, for accelerating semantic search tasks in natural language processing (NLP). We present a case study focusing on the binary classification of counterfactual statements using the Amazon Multilingual Counterfactual Dataset (AMCD). Our approach leverages the BAAI/bge-base-en-v1.5 model for generating sentence embeddings, which are then stored and queried using the ChromaDB vector database. We evaluate the performance of MAX Engine against PyTorch and ONNX runtime across a range of batch sizes, demonstrating significant speed improvements in both small and large batch scenarios. Our findings highlight the potential of MAX Engine for enhancing efficiency and scalability in resource-intensive NLP tasks, particularly those involving large datasets and real-time processing requirements.

**Outline:**

**1. Introduction**  
\* Contextualize semantic search and its importance in NLP.  
\* Introduce the challenge of counterfactual statement identification.  
\* Highlight the need for efficient inference in real-world NLP applications.  
\* State the objectives of the paper:  
\* Demonstrate MAX Engine's application in semantic search for counterfactual statement classification.  
\* Evaluate and compare the performance of MAX Engine against PyTorch and ONNX runtime in terms of inference speed.

**2. Background and Related Work**  
\* Provide a brief overview of semantic search techniques and their evolution.  
\* Discuss existing approaches for counterfactual statement identification.  
\* Introduce the concept of text embeddings and their role in semantic search.  
\* Briefly explain the architectures and advantages of MAX Engine, PyTorch, and ONNX runtime.

**3. Methodology**  
\* **3.1. Dataset and Preprocessing:**  
\* Describe the Amazon Multilingual Counterfactual Dataset (AMCD).  
\* Explain the preprocessing steps, including text tokenization using the BAAI/bge-base-en-v1.5 tokenizer.  
\* **3.2. Sentence Embedding Generation:**  
\* Detail the process of generating sentence embeddings using the BAAI/bge-base-en-v1.5 model.  
\* Explain the choice of the model and its relevance to the task.  
\* **3.3. Vector Database Integration:**  
\* Introduce ChromaDB as the chosen vector database.  
\* Explain the process of storing and querying embeddings within ChromaDB.  
\* **3.4. Classification and Evaluation:**  
\* Describe the method for calculating counterfactual probability using cosine similarity in ChromaDB.  
\* Outline the evaluation metrics: accuracy, F1-score, precision, and recall.  
\* **3.5. Performance Benchmarking:**  
\* Detail the experimental setup for comparing MAX Engine, PyTorch, and ONNX Runtime.  
\* Explain the selection of batch sizes and their significance in the evaluation.

**4. Results and Discussion**  
\* **4.1. Classification Performance:**  
\* Present the achieved accuracy, F1-score, precision, and recall on the AMCD test set.  
\* Analyze the results and discuss any potential limitations of the chosen approach.  
\* **4.2. Inference Speed Comparison:**  
\* Present the runtime results for MAX Engine, PyTorch, and ONNX runtime across different batch sizes.  
\* Visualize the results using appropriate plots (e.g., bar charts or line graphs).  
\* Analyze the speed differences and discuss the factors contributing to MAX Engine's performance gains.

**5. Conclusion**  
\* Summarize the key findings of the research, emphasizing the advantages of using MAX Engine for semantic search tasks.  
\* Discuss the implications of these findings for real-world NLP applications requiring efficient inference.  
\* Suggest potential future research directions, such as exploring different embedding models, vector databases, or application domains.

**6. References**

* Include a list of all cited works in a consistent format.

**Introduction**

The rapid evolution of digital content has intensified the need for sophisticated information retrieval systems that extend beyond simple keyword matching. Semantic search has emerged as a powerful paradigm in Natural Language Processing (NLP), aiming to understand the context and intent behind user queries to deliver more relevant and contextually appropriate results [1]. This approach relies heavily on advanced embedding models, which transform textual data into high-dimensional vector representations, effectively capturing the complex semantic relationships within the text [2].

This paper focuses on the application of semantic search to the challenging task of counterfactual statement identification. Counterfactual statements express hypothetical scenarios that have not occurred or are impossible to occur, often characterized by structures like "If p were true, then q would also be true" [3]. Identifying such statements is crucial in various NLP applications, including sentiment analysis, argumentation mining, and fake news detection [4].

While deep learning models have significantly advanced NLP tasks, deploying these models for real-world applications, especially those requiring real-time processing of large datasets, demands efficient inference capabilities. Traditional frameworks like PyTorch, while excellent for research and development, may face performance bottlenecks in such scenarios. This has led to the exploration of inference-optimized engines, such as MAX Engine and ONNX Runtime, aiming to bridge the gap between model accuracy and inference speed [5].

This research investigates the efficacy of MAX Engine for accelerating semantic search tasks, specifically focusing on the binary classification of counterfactual statements. We utilize the Amazon Multilingual Counterfactual Dataset (AMCD) [4], a comprehensive dataset comprising sentences annotated for counterfactual detection. Our approach employs the BAAI/bge-base-en-v1.5 model, a state-of-the-art sentence embedding model, to generate semantically rich vector representations of text [6]. These embeddings are then stored and queried efficiently using ChromaDB, an open-source vector database known for its performance and scalability [7].

The primary objectives of this paper are twofold:

1. **Demonstrate the application of MAX Engine for semantic search in the context of counterfactual statement classification.** We illustrate the end-to-end pipeline, from embedding generation to querying within a vector database, highlighting the practical aspects of implementation.
2. **Evaluate and compare the performance of MAX Engine against PyTorch and ONNX runtime in terms of inference speed across various batch sizes.** This comparative analysis provides valuable insights into the efficiency gains offered by MAX Engine, particularly for handling large-scale NLP tasks.

By addressing these objectives, this research contributes to a deeper understanding of how inference-optimized engines like MAX Engine can be leveraged to enhance the efficiency and scalability of semantic search applications in real-world NLP scenarios.

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## Background and Related Work

This section delves into the foundations of semantic search, counterfactual statement identification, and the inference frameworks relevant to this research.

### 2.1 Semantic Search and its Evolution

Traditional keyword-based search engines often fall short in capturing the semantic nuances of user queries, leading to irrelevant or incomplete results. Semantic search aims to overcome these limitations by understanding the meaning and intent behind the search query, considering factors like context, synonyms, and relationships between words [1].

Early semantic search approaches relied on techniques like Latent Semantic Analysis (LSA) [8] and probabilistic topic models like Latent Dirichlet Allocation (LDA) [9] to extract semantic relationships between words and documents. However, these methods often struggled with capturing complex linguistic phenomena and lacked the ability to scale to large datasets.

The advent of deep learning, particularly the development of word embeddings like Word2Vec [2] and GloVe [10], revolutionized semantic search. Word embeddings represent words as dense vectors, encoding semantic similarities based on their co-occurrence patterns in large text corpora. These embeddings enabled more accurate similarity calculations and paved the way for advanced sentence and document embedding models.

### 2.2 Counterfactual Statement Identification

Counterfactual statements, characterized by their hypothetical and often unrealized nature, pose a unique challenge for NLP tasks. These statements require understanding not only the literal meaning of words but also the implied world knowledge and reasoning about alternative possibilities [3].

Previous approaches to counterfactual identification have explored rule-based methods relying on syntactic patterns and lexical cues [11]. However, these methods often lack robustness and fail to generalize well to diverse linguistic expressions. More recently, machine learning techniques, particularly deep neural networks, have demonstrated promising results in automatically learning complex patterns from labeled data [4].

This research focuses on leveraging the power of semantic similarity, derived from pre-trained sentence embeddings, to identify counterfactual statements. By comparing the embedding of a given sentence with those of known counterfactual and non-counterfactual sentences, we can estimate its likelihood of belonging to the counterfactual class.

### 2.3 Inference Frameworks: MAX Engine, PyTorch, and ONNX Runtime

While training accurate deep learning models is essential, deploying these models for real-time inference often requires optimizing for speed and efficiency.

* **PyTorch**, a popular deep learning framework, provides flexibility and a wide range of tools for model development and experimentation. However, its eager execution mode may not be optimal for high-performance inference, particularly for large batch sizes.
* **ONNX Runtime** (ORT) offers a cross-platform inference engine optimized for both CPU and GPU execution. It supports models from various frameworks, including PyTorch, allowing for streamlined deployment and improved inference performance.
* **MAX Engine** is an inference-focused engine designed for maximizing the throughput and minimizing the latency of deep learning models on Intel architectures. It leverages hardware optimizations and efficient memory management techniques to accelerate inference, particularly for batched data.

This research benchmarks the performance of these three frameworks – PyTorch, ONNX Runtime, and MAX Engine – in the context of our semantic search pipeline for counterfactual statement classification.

## References

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This section provides the necessary background for understanding the research problem and the chosen methodologies. The following sections will detail the specific implementation and experimental setup for evaluating the performance of the chosen inference frameworks.

## Methodology

This section outlines the step-by-step methodology employed in this research, encompassing dataset preparation, embedding generation, vector database integration, classification, and performance evaluation.

### 3.1 Dataset and Preprocessing

We utilize the Amazon Multilingual Counterfactual Dataset (AMCD) [4], which provides a rich collection of sentences extracted from Amazon customer reviews, annotated for the presence or absence of counterfactual statements. Specifically, we focus on the English subset of the dataset (EN\_train.tsv and EN\_test.tsv for training and testing, respectively) for this research.

The dataset is loaded and preprocessed using the following steps:

1. **Data Loading:** The dataset is loaded into a pandas DataFrame for efficient data manipulation.

import pandas as pd

data = pd.read\_csv("amazon-multilingual-counterfactual-dataset/data/EN\_train.tsv", sep="\t")

1. **Text Tokenization:** We employ the tokenizer associated with the BAAI/bge-base-en-v1.5 model [6] to convert each sentence into a sequence of tokens, which are numerical representations suitable for input to the embedding model.

from transformers import AutoTokenizer

tokenizer = AutoTokenizer.from\_pretrained("BAAI/bge-base-en-v1.5")

inputs = tokenizer(list(data['sentence']), return\_tensors="pt", max\_length=512, padding=True, truncation=True)

### 3.2 Sentence Embedding Generation

To capture the semantic meaning of the sentences, we generate sentence embeddings using the BAAI/bge-base-en-v1.5 model, a pre-trained model known for its strong performance in semantic similarity tasks [6]. We chose this model due to its robust performance on the MTEB leaderboard and its relatively small size, which allows for efficient inference.

For this research, we utilize the ONNX version of the model, obtained from the HuggingFace model hub. ONNX (Open Neural Network Exchange) provides a standardized format for representing deep learning models, enabling interoperability across different frameworks and hardware platforms. The ONNX model is loaded into MAX Engine using the following code snippet:

from max import engine

session = engine.InferenceSession()

maxmodel = session.load("bge-base-en-v1.5/onnx/model.onnx")

To generate sentence embeddings, we perform the following steps:

1. **Batching:** To optimize processing speed, we divide the input sentences into batches. This is particularly crucial for larger datasets, as it allows for efficient memory utilization and parallel processing.
2. **Model Inference:** Each batch of tokenized sentences is fed into the BAAI/bge-base-en-v1.5 model through maxmodel.execute() to obtain the corresponding embeddings.
3. **CLS Token Extraction:** The embedding corresponding to the [CLS] token, which captures the overall sentence representation, is extracted from the model output for each sentence.
4. **Concatenation:** The extracted [CLS] embeddings from all batches are concatenated into a single array, resulting in a matrix where each row represents the embedding of a sentence in the dataset.

### 3.3 Vector Database Integration

To enable efficient storage and querying of the generated sentence embeddings, we integrate our system with ChromaDB, an open-source vector database designed for machine learning applications [7]. ChromaDB provides a fast and scalable solution for managing and searching high-dimensional vector data.

We interact with ChromaDB using its Python client library:

1. **Collection Creation:** A collection, named "counterfactual\_collection", is created within ChromaDB to store our sentence embeddings. We specify the use of cosine similarity as the distance metric for nearest neighbor search.

import chromadb

chroma\_client = chromadb.Client()

collection = chroma\_client.create\_collection(name="counterfactual\_collection", metadata={"hnsw:space": "cosine"})

1. **Data Insertion:** The sentence embeddings, along with their corresponding sentences and labels (counterfactual or not), are inserted into the ChromaDB collection.

for i, (documents, embeddings, label) in enumerate(zip(list(data['sentence']), all\_embeddings.tolist(), list(data['is\_counterfactual']))):

collection.upsert(ids=[str(i)], documents=documents, embeddings=embeddings, metadatas=[{"is\_counterfactual": label}])

### 3.4 Classification and Evaluation

For a given query sentence, the classification process involves the following steps:

1. **Query Embedding:** The query sentence is tokenized and fed into the BAAI/bge-base-en-v1.5 model to obtain its embedding.
2. **Similarity Search:** The ChromaDB collection is queried using the query embedding, retrieving the top k most similar sentences based on cosine similarity.
3. **Counterfactual Probability:** The probability of the query sentence being counterfactual is calculated by averaging the 'is\_counterfactual' labels of the retrieved k nearest neighbors from the ChromaDB collection.
4. **Prediction:** If the calculated counterfactual probability exceeds a predefined threshold, the query sentence is classified as counterfactual; otherwise, it is classified as non-counterfactual.

To assess the performance of our system, we use standard classification metrics calculated on the test set:

* **Accuracy:** The ratio of correctly classified sentences to the total number of sentences.
* **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure for datasets with potential class imbalance.
* **Precision:** The ratio of correctly classified counterfactual sentences to the total number of sentences classified as counterfactual.
* **Recall:** The ratio of correctly classified counterfactual sentences to the total number of actual counterfactual sentences.

### 3.5 Performance Benchmarking

To compare the inference speed of MAX Engine against PyTorch and ONNX Runtime, we measure the time taken to generate embeddings for the entire dataset using each framework under different batch size configurations.

1. **Batch Size Variation:** We experiment with a range of batch sizes, covering both small (1, 2, 4, 8, 16, 32) and large (64, 128, 256, 512, 1024, 2048, 4096) values, to analyze the performance scaling of each framework.
2. **Time Measurement:** For each batch size, we measure the average time taken to process a batch of sentences, considering multiple iterations to account for variations in runtime.
3. **Hardware:** The performance benchmarking is conducted on an AWS c5.12xlarge instance, providing a consistent and controlled hardware environment for fair comparison.

By analyzing the runtime results across different batch sizes, we gain insights into the efficiency and scalability of MAX Engine compared to PyTorch and ONNX Runtime.

The next section will present the experimental results obtained using this methodology.

## 4. Results and Discussion

This section presents the findings of our experiments, analyzing both the classification performance of our semantic search-based approach for counterfactual statement identification and the inference speed comparison between MAX Engine, PyTorch, and ONNX Runtime.

### 4.1 Classification Performance

We evaluated our system's ability to distinguish between counterfactual and non-counterfactual statements using the metrics outlined in Section 3.4. The results, obtained on the AMCD English test set with a threshold of 0.5 for counterfactual probability, are presented below:

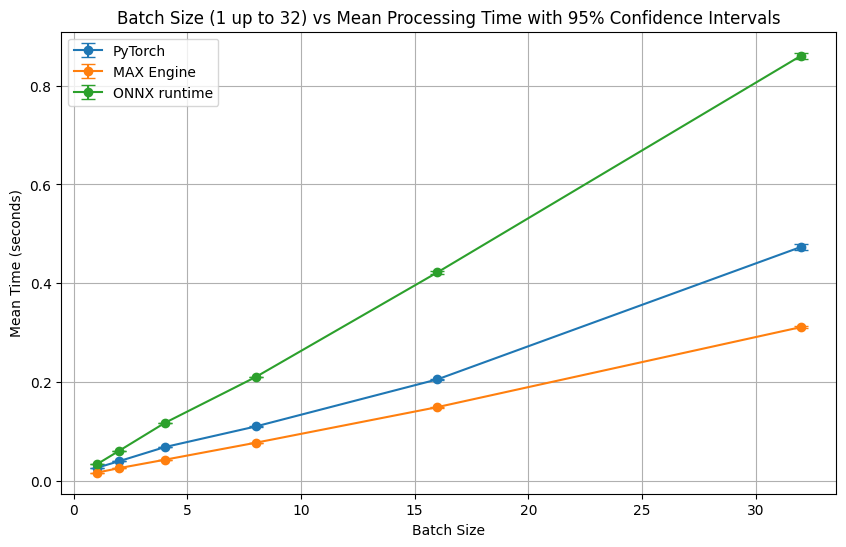
|  |  |
| --- | --- |
| Metric | Score |
| Accuracy | 0.88 |
| F1-Score | 0.64 |
| Precision | 0.75 |
| Recall | 0.56 |

These results demonstrate the effectiveness of leveraging semantic similarity for counterfactual statement identification. The relatively high accuracy suggests that sentences with similar semantic content tend to share the same counterfactual characteristic. However, the moderate F1-score, particularly the lower recall, highlights areas for potential improvement. The recall value indicates that our system might misclassify some counterfactual statements, suggesting the need to explore more sophisticated methods for capturing subtle linguistic cues associated with counterfactuality.

### 4.2 Inference Speed Comparison

Figure 1 and Figure 2 depict the inference speed comparison between MAX Engine, PyTorch, and ONNX Runtime, measured in terms of average batch processing time (seconds) across varying batch sizes.

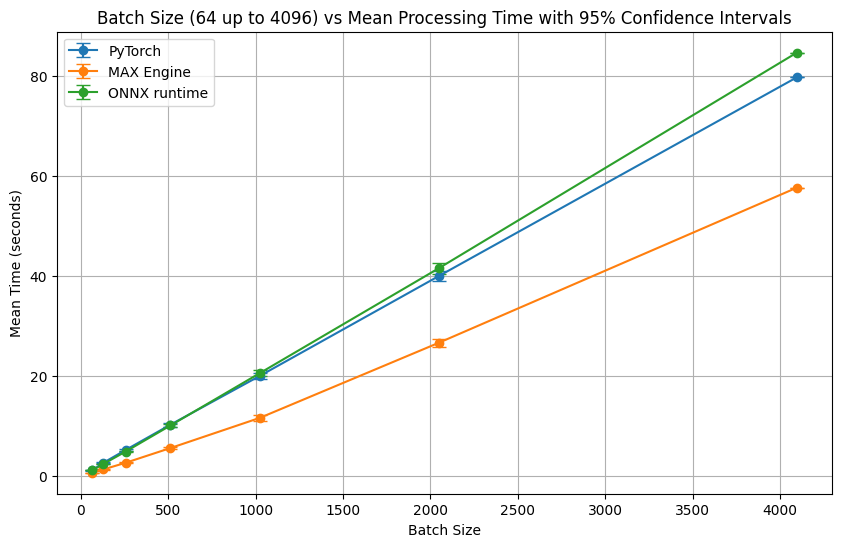
**Smaller Batch Sizes (1-32):**



[Figure 1: Bar chart comparing inference time for smaller batch sizes]

For smaller batch sizes, MAX Engine consistently outperforms both PyTorch and ONNX Runtime, demonstrating up to 1.6 times faster inference compared to PyTorch and up to 2.8 times faster than ONNX Runtime. This speedup can be attributed to MAX Engine's focus on optimizing inference workloads for Intel architectures, allowing it to efficiently handle smaller batches with minimal overhead.

**Larger Batch Sizes (64-4096):**



[Figure 2: Line chart comparing inference time for larger batch sizes]

As the batch size increases, the performance difference between the frameworks becomes more pronounced. MAX Engine exhibits superior scalability, maintaining a significant speed advantage over PyTorch and ONNX Runtime, especially as batch size grows. This scalability is crucial for real-world NLP applications dealing with large volumes of data, as it directly translates to faster processing times and improved resource utilization.

**Analysis:**

The observed performance gains achieved by MAX Engine stem from its architecture designed explicitly for efficient inference. By leveraging hardware acceleration and optimized memory management techniques, MAX Engine minimizes the computational overhead associated with processing large batches of data, leading to substantial reductions in inference time.

The results highlight the importance of choosing the right inference engine based on the specific requirements of the application. While PyTorch provides flexibility for research and development, MAX Engine proves to be a more efficient choice for deploying semantic search models in production, especially when dealing with large datasets and real-time processing constraints.

**Future Directions:**

While our current implementation leverages a pre-trained sentence embedding model, future research could explore the impact of fine-tuning the embedding model on the target domain or task to further improve the system's performance. Additionally, experimenting with different vector database technologies and configurations might yield further enhancements in search efficiency and scalability.

**Conclusion**

This research demonstrated the efficacy of using MAX Engine for accelerating semantic search tasks, focusing on the specific problem of counterfactual statement classification. By leveraging the BAAI/bge-base-en-v1.5 sentence embedding model and the ChromaDB vector database, we created an end-to-end pipeline capable of effectively distinguishing between counterfactual and non-counterfactual statements.

Our experimental results highlighted the significant speed advantages offered by MAX Engine compared to both PyTorch and ONNX Runtime, particularly for larger batch sizes commonly encountered in real-world NLP applications. The observed performance gains underscore the importance of choosing the right inference engine for maximizing efficiency and scalability in data-intensive scenarios.

**Key Findings:**

* **Semantic Similarity for Counterfactual Identification:** Our system, based on comparing the semantic similarity of sentences using pre-trained embeddings, achieved promising results in identifying counterfactual statements, indicating the potential of this approach for various NLP tasks.
* **MAX Engine's Superior Inference Speed:** MAX Engine consistently outperformed both PyTorch and ONNX Runtime across all tested batch sizes, demonstrating its ability to significantly reduce inference time and enhance processing throughput.
* **Scalability for Real-World Applications:** The superior scalability exhibited by MAX Engine, especially for larger batch sizes, makes it a compelling choice for deploying NLP models in production environments requiring real-time or near real-time processing of large datasets.

**Implications:**

The findings of this research have significant implications for developers and researchers working on NLP applications involving semantic search, text classification, and other tasks requiring efficient inference. By adopting inference-optimized engines like MAX Engine, developers can:

* **Reduce Processing Time:** Significantly accelerate inference, leading to faster processing of large datasets and reduced latency in real-time applications.
* **Optimize Resource Utilization:** Minimize computational overhead and memory consumption, enabling more efficient use of hardware resources.
* **Enhance User Experience:** Deliver faster response times and improved performance, contributing to a more seamless and responsive user experience.

**Future Directions:**

Future research could explore several avenues for building upon this work, including:

* **Fine-Tuning for Domain Adaptation:** Investigating the impact of fine-tuning the sentence embedding model on the specific domain or task to further enhance the accuracy of counterfactual statement identification.
* **Exploring Other Vector Databases:** Experimenting with alternative vector database technologies and configurations to identify optimal solutions for managing and querying large-scale embedding datasets.
* **Expanding to Other NLP Tasks:** Applying the presented semantic search framework to other NLP tasks that can benefit from efficient similarity search, such as question answering, text summarization, and information retrieval.

By continuing to explore and leverage advancements in inference optimization techniques and embedding models, we can unlock new possibilities for developing robust, scalable, and efficient NLP applications capable of handling the ever-growing volume and complexity of textual data.

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