

Embedding Gemma 2

A Technical Guide to Google's Embedding Model for Semantic Search and RAG

Learn how to understand and deploy EmbeddingGemma 2 for semantic search, retrieval-augmented generation, code retrieval and multimodal applications, with practical examples and production-ready code.



DANIEL BROOKS

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Contents

- A Technical Guide to Google’s Embedding Model for Semantic Search and RAG** 1
- Introduction** 2
- Chapter 1: What Is an Embedding Model?** 4
 - What Is a Vector Representation? 4
 - From Words to Meaning: How Embeddings Encode Semantics . . . 5
 - Similarity as Geometry: Distance Metrics in Vector Space 6
 - Embedding Models vs Generative Models 7
 - Where Embeddings Are Used in Practice 8
- Chapter 2: How Transformers Generate Embeddings** 11
 - Transformer Architecture in Brief 11
 - Self-Attention and Semantic Understanding 12
 - Tokenization and Context Windows 13
 - From Sequence Output to Vector Embedding 14
 - Why Transformers Excel at Semantic Encoding 15
- Chapter 3: The Embedding Pipeline: Pooling, Normalization and Beyond** 17
 - Mean Pooling and Token Aggregation 17
 - CLS and EOS Token Embeddings 17
 - L2 Normalization and Its Effect 17
 - Matryoshka Representation Learning: Truncatable Embeddings . . 17
 - Output Dimensions and Task Adaptation 17
- Chapter 4: The Evolution of Embedding Models** 18
 - Static Word Embeddings: Word2Vec and GloVe 18
 - Contextual Embeddings: BERT and Its Successors 18
 - Task-Specific Embedding Models 18

CONTENTS

The Rise of Instruction-Tuned Embeddings	18
Benchmarking and Competition in the Era of Open Models	18
Chapter 5: Enter EmbeddingGemma: The Original Model	19
EmbeddingGemma Release and Architecture	19
Performance and Benchmarks	19
Strengths and Limitations	19
Why a Second Generation Was Needed	19
How EmbeddingGemma Differs from Base Gemma Models	19
Chapter 6: Introducing EmbeddingGemma 2	20
Release Details and Model Family	20
Parameter Count and Architecture Overview	20
Embedding Dimensions and Matryoshka Support	20
Supported Input Modalities	20
Licensing and Intended Use	20
Chapter 7: Architecture Deep Dive	21
Base Architecture: Gemma-Style Transformer	21
Encoder Configuration and Hyperparameters	21
Self-Attention Variants	21
Embedding Layers and Positional Encoding	21
Text and Multimodal Encoder Design	21
Chapter 8: Multilingual and Code Capabilities	22
Language Coverage and Training Data	22
Performance Across Languages	22
Code Embedding Capabilities	22
Practical Considerations for Multilingual Deployment	22
Known Limitations	22
Chapter 9: Context Window and Input Handling	23
Context Window Size and Tokenization	23
Character and Token Limits	23
Instruction Prefixes and Task Formatting	23
Document Chunking Strategies	23
Query Encoding Best Practices	23
Chapter 10: Training Methodology	24
Training Objectives and Loss Functions	24

CONTENTS

Contrastive Learning Setup	24
Data Sources and Diversity	24
Instruction Tuning Procedure	24
Matryoshka Representation Learning Integration	24
Chapter 11: Benchmarks and Performance	25
MTEB Benchmark Results	25
Cross-Lingual Benchmarks	25
Retrieval and RAG Benchmarks	25
Code and Multimodal Benchmarks	25
Critical Assessment of Reported Results	25
Chapter 12: Computational Requirements and Resource Planning	26
VRAM and Memory Footprint	26
CPU vs GPU Inference	26
Hardware Recommendations by Scale	26
Quantization and Efficiency Options	26
Cost Estimation for Production Workloads	26
Chapter 13: Comparison with Competing Models	27
Closed-Source API Models	27
Open-Source Alternatives	27
Retrieval Quality Comparison	27
Latency and Throughput Comparison	27
Cost and TCO Analysis	27
Selection Decision Matrix	27
Chapter 14: Use Case Analysis	29
Core Strengths: Semantic Search and RAG	29
Document and Code Search	29
Multilingual and Cross-Lingual Applications	29
Multimodal Use Cases	29
Edge Cases and Unsuitable Scenarios	29
Recommendation and Clustering Applications	29
Chapter 15: Getting Started: Environment and Installation	31
Hardware and Software Prerequisites	31
Python Environment Setup	31
Model Acquisition and Download	31
Basic Initialization and Inference	31

Verification and Troubleshooting	31
Chapter 16: Generating Embeddings: A Practical Guide	32
Preprocessing Text for Embedding	32
Task-Specific Prompt Formatting	32
Batching for Efficiency	32
Handling Long Documents	32
Error Handling and Edge Cases	32
Chapter 17: Similarity, Retrieval and Vector Search	33
Cosine Similarity and Dot Product	33
Approximate Nearest Neighbor Search	33
Vector Database Integration	33
Hybrid Retrieval and Metadata Filtering	33
Tuning Retrieval Thresholds	33
Chapter 18: Vector Databases and Indexing	34
Choosing a Vector Database	34
Pinecone, Qdrant, Weaviate and Milvus	34
Local and Self-Hosted Options	34
Index Configuration and Optimization	34
Scaling Considerations	34
Chapter 19: Reference Implementation: Semantic Search Engine	35
System Architecture and Design	35
Data Preparation and Chunking	35
Embedding Generation Pipeline	35
Index Construction	35
Search Query Processing	35
Evaluation and Validation	35
Chapter 20: Reference Implementation: Production RAG Pipeline	37
RAG Architecture Overview	37
Document Ingestion Pipeline	37
Retrieval Configuration and Tuning	37
Integration with LLMs	37
Evaluation Metrics and Monitoring	37
Deployment Considerations	37
Chapter 21: Reference Implementation: Code Search System	39

CONTENTS

Understanding Code Retrieval Challenges	39
Code Preprocessing and Chunking	39
Repository Indexing Strategy	39
Query Understanding for Code Search	39
Integration with Development Workflows	39
Chapter 22: Reference Implementation: Multimodal Search	40
Multimodal Embedding Concepts	40
Image-to-Text and Text-to-Image Retrieval	40
Audio and Video Indexing	40
Query Processing Across Modalities	40
Limitations and Quality Considerations	40
Chapter 23: Engineering Quality and Best Practices	41
Chunk Size and Overlap Tuning	41
Metadata Design and Preservation	41
Embedding Consistency and Versioning	41
Evaluation Frameworks	41
Monitoring and Alerting	41
Cost Optimization Strategies	41
Chapter 24: Troubleshooting and Failure Modes	43
Diagnosing Poor Retrieval Quality	43
False Positives and False Negatives	43
Multilingual Performance Issues	43
Performance and Latency Troubleshooting	43
Memory and Resource Problems	43
Model Updates and Index Migration	43
Diagnostic Checklist	44
Chapter 25: Deployment, Adoption and Future Outlook	45
Deployment Checklists by Scale	45
Model Selection Framework	45
Recommended Configurations	45
Security and Compliance Considerations	45
Monitoring for Model Updates	45
Future Outlook and Relevance	45
Conclusion	47

References 48

A Technical Guide to Google's Embedding Model for Semantic Search and RAG

A practical, evidence-based guide to understanding and deploying EmbeddingGemma 2 for production semantic search, retrieval-augmented generation, code retrieval and multimodal applications. This book explains the model's architecture, capabilities and constraints in depth, provides detailed implementation walkthroughs with complete code examples and helps you make informed decisions about where and how EmbeddingGemma 2 fits into your technical stack.

Introduction

In the space of a single year, embedding models went from being a specialized component for information retrieval to a foundational building block of almost every modern AI application. Retrieval-augmented generation, semantic search, recommendation engines, code assistance tools and increasingly multimodal systems all depend on one core operation: converting diverse inputs into vectors that capture meaning, then finding the vectors that are closest to a query in a high-dimensional space.

When Google DeepMind released EmbeddingGemma in September 2025, it was a focused contribution: a compact, text-only embedding model optimized for on-device deployment. By October 2026, the second generation, EmbeddingGemma 2, represented something significantly different. It is a natively multimodal model that maps text, code, images, video frames and audio into a single, shared 768-dimensional embedding space while remaining small enough to run on consumer hardware. At 740 million parameters in its full configuration, it is designed for a specific class of use case: applications that need strong retrieval quality, offline capability and low infrastructure cost without accepting the constraints of proprietary API services.

This book is written for engineers and architects who need to do more than call an embedding API. It is for people who are building retrieval systems that must survive production conditions, choosing between embedding models for different workloads, tuning chunking and indexing strategies, or deploying models on constrained hardware. You will find rigorous technical analysis grounded in official documentation, published benchmarks and verified implementations. Every claim about EmbeddingGemma 2's capabilities, performance, or resource requirements is backed by sources.

The central argument is straightforward. EmbeddingGemma 2 is an excellent choice for teams that need an open multimodal embedding model that runs locally with predictable costs. Its combination of Gemma 4 architecture, Matryoshka Representation Learning and modular encoder loading gives it a flexibility profile that larger or closed-source models cannot match. But it is not universally optimal. It has precision requirements that bite if you ignore them, dimensionality constraints that matter for multimodal workloads and

performance characteristics that are competitive rather than dominant. A good embedding strategy depends on understanding both what the model can do and where it falls short.

The book is organized as a learning path. The first section establishes the foundations: what embeddings are, how transformers produce them and how the embedding pipeline works. The second section examines EmbeddingGemma 2 in detail: its architecture, training, benchmarks and comparison to alternatives. The third section focuses on implementation with concrete code examples, covering installation, inference, vector indexing and evaluation. The fourth section presents complete reference implementations for semantic search, retrieval-augmented generation, code search and multimodal search. The final section consolidates engineering best practices and deployment guidance.

No single chapter is self-contained. They build on each other, so reading in order is recommended. If you are already comfortable with embeddings and want to jump directly to implementation, Chapters 15 through 22 are where the practical work begins. But even experienced practitioners will find value in the analysis of Matryoshka truncation behavior, precision requirements and the model's actual benchmark standing relative to competitors.

The goal is not to tell you whether to use EmbeddingGemma 2. The goal is to give you enough technical understanding that you can make that decision yourself and build a system that works when it matters.

Chapter 1: What Is an Embedding Model?

What Is a Vector Representation?

Consider a simple problem: you have a database of product descriptions and a user types a search query in their own words. Keyword matching fails when the vocabulary diverges. A user might type “affordable running shoes” while the product description says “budget-friendly jogging sneakers.” Neither phrase shares exact words with the other yet they mean essentially the same thing.

The solution is to represent text not as sequences of characters but as vectors of numbers, where semantically similar items end up near each other in a high-dimensional geometric space. This is the core idea behind embeddings.

An embedding is a dense numerical representation of a piece of data. For text, it is typically a fixed-length vector of floating-point numbers, often hundreds or thousands of dimensions. Each individual dimension does not correspond to any interpretable feature like “about animals” or “formal tone.” Instead, the geometry of the entire vector space encodes meaning implicitly. When two items have similar vectors, they are similar in some sense relevant to the task the model was trained for.

The analogy often used is language. In a well-constructed embedding space, the relationship between “king” and “queen” mirrors the relationship between “man” and “woman.” The vector arithmetic roughly holds: the vector for king minus the vector for man approximately equals the vector for queen minus the vector for woman. This is not magic. It is the emergent result of training a model to predict which pieces of text co-occur in context. The model learns to place related concepts near each other and distant concepts far apart.

The key property that makes embeddings useful is continuity. Small changes in meaning produce small changes in vector values. This allows you to use simple distance calculations to find similar items without needing to understand the content semantically. You do not parse syntax or extract features. You compute a vector and search for neighbors.

For this book, the primary type of embedding we are discussing is a text embedding: a vector that represents the meaning of a sentence, paragraph, document, or query. EmbeddingGemma 2 also produces embeddings for images, audio and video, but the fundamental principle is the same. Each modality is mapped into the same vector space so that cross-modal similarity becomes possible. A text query like “a sunset over mountains” can be compared directly to an image embedding and similar items cluster together regardless of their original format.

Vector embeddings differ fundamentally from sparse representations like word counts or TF-IDF vectors. A sparse representation has one dimension per vocabulary term, is mostly zeros and captures only explicit lexical overlap. A dense embedding has a fixed, relatively small number of dimensions, is nearly full and captures implicit semantic relationships. This difference is what makes modern semantic search possible.

From Words to Meaning: How Embeddings Encode Semantics

The transition from raw text to a meaningful vector representation depends on the architecture and training process of the embedding model. Early approaches used static word embeddings like Word2Vec or GloVe, where every occurrence of a word received the same vector regardless of context. The word “bank” had one vector whether it appeared in “river bank” or “bank account.” This worked reasonably well for many applications but could not handle ambiguity.

Modern embedding models, including EmbeddingGemma 2, use transformer architectures that produce contextual embeddings. Every token in the input gets its own representation conditioned on all the other tokens. The word “bank” in a financial context receives a different vector from “bank” in a geographical context. The embedding is not about the word in isolation but about the word as it functions in this specific sentence.

Training these models is where the semantic understanding comes from. The most common approach is a form of self-supervised learning. The model is trained on massive amounts of text to predict which sentences are similar or dissimilar, often by contrasting positive pairs (sentences that mean the same thing) against negative pairs (sentences chosen at random). Over billions of

examples, the model adjusts its internal parameters so that semantically similar inputs produce similar vectors and dissimilar inputs produce distant vectors.

For a model like EmbeddingGemma 2, this training is augmented with instruction tuning. Short prefixes like “task: search result | query:” are prepended to inputs to signal the intended use. This guides the model to produce representations optimized for that specific task rather than a generic notion of similarity. A vector produced for a search query encodes information differently from a vector produced for a document meant to be retrieved, which is why retrieval systems typically use asymmetric encoding: one embedding strategy for queries and another for documents.

The resulting embeddings capture multiple levels of information simultaneously. They encode lexical content, syntactic structure, pragmatic intent and domain-specific patterns. The model does not understand language in the human sense. It has learned statistical regularities that happen to correspond to something like understanding for many practical purposes. This distinction matters because it explains why embeddings can fail in predictable ways. They reflect the data they were trained on and the optimization objective they were trained for. If your use case falls outside those boundaries, quality degrades.

For EmbeddingGemma 2 specifically, the training includes code as well as natural language, which means its embeddings capture programmatic structure alongside semantic meaning. Functions with similar behavior but different names end up near each other. This enables code retrieval that works beyond simple keyword matching. The same training also includes data from over 100 languages, giving the model cross-lingual alignment where similar concepts in different languages map to similar regions of the vector space.

Similarity as Geometry: Distance Metrics in Vector Space

Once you have embeddings, the central operation is measuring how similar two vectors are. This reduces to a geometry problem in high-dimensional space.

The most common metric is cosine similarity. Cosine similarity computes the cosine of the angle between two vectors, ignoring their magnitude and focusing purely on direction. The result ranges from -1 (completely opposite) to 1 (identical direction), with 0 indicating orthogonality or no similarity. For text embeddings, cosine similarity works well because the direction of the vector

encodes meaning while the magnitude often does not. Most modern embedding models, including EmbeddingGemma 2, produce normalized vectors with unit length. When vectors are normalized, cosine similarity is mathematically equivalent to the dot product, which simplifies computation.

Euclidean distance is another option. It measures the straight-line distance between two points. For non-normalized vectors, Euclidean distance captures both directional and magnitude differences. For normalized vectors, it is monotonically related to cosine similarity, so ranking results by Euclidean distance produces the same ordering as ranking by cosine similarity. The choice between them is mostly a matter of implementation convenience.

There are subtleties that matter in practice. EmbeddingGemma 2's model card emphasizes that truncated embeddings from Matryoshka Representation Learning must be re-normalized after truncation. Simply cutting off dimensions without re-normalization distorts the geometry and degrades retrieval quality. The truncation preserves the leading dimensions (which contain the most signal), but the resulting shorter vector no longer has unit length, so a final normalization step is required.

The dimensionality of the embedding space affects both quality and cost. Higher dimensions can represent more nuanced distinctions but require more storage and slower search. EmbeddingGemma 2 outputs 768 dimensions by default but supports truncation to 512, 256, or 128 dimensions via MRL. The trade-off is not linear. Dropping to 512 dimensions often has minimal quality impact while reducing storage by one third. Dropping to 128 dimensions cuts storage sixfold but introduces meaningful degradation, especially for multimodal tasks.

Understanding similarity metrics is essential because the choice you make affects not just the code but the design of your vector index. Approximate nearest neighbor algorithms like HNSW optimize for specific distance functions and configuration parameters behave differently depending on whether you are using cosine similarity or Euclidean distance. This matters for production systems where milliseconds of latency and basis points of recall difference translate into real user experience and cost differences.

Embedding Models vs Generative Models

A frequent source of confusion, especially for people new to the ecosystem, is the distinction between embedding models and generative language models.

Both are built on transformer architectures. Both are trained on large text corpora. Both can be hundreds of millions or billions of parameters in size. But they serve fundamentally different purposes.

Generative models like GPT-4, Claude, or Gemma produce text as output. You give them a prompt and they autoregressively generate tokens one at a time to form a response. The output is human-readable language: answers, summaries, code, creative writing. The model's capability is measured in terms of reasoning, coherence, instruction following and factual accuracy.

Embedding models produce vectors as output. You give them text (or images, audio, video) and they return a fixed-length numerical vector with no generative capability. The output is not human-readable. It is designed to be used as input to a retrieval system, classifier, or clustering algorithm. The model's capability is measured in terms of retrieval quality, semantic discrimination, cross-modal alignment and computational efficiency.

This distinction has practical consequences. A generative model can answer your question directly. An embedding model cannot. But an embedding model can help you find the right document to give to a generative model, which is the basis of retrieval-augmented generation. RAG systems combine both: the embedding model retrieves relevant context and the generative model produces a grounded response based on that context.

For EmbeddingGemma 2 specifically, it is important to be clear: it is not a generative model. It will not write text, answer questions, or generate code. It produces embeddings that enable retrieval. If you want a generative companion from the same family, you would pair it with a Gemma 4 decoder model. Google's own documentation positions EmbeddingGemma 2 for search, routing, retrieval, classification and clustering. Generation is not on that list.

The confusion sometimes arises because both model types are distributed through the same channels like Hugging Face and often share architectural lineage. EmbeddingGemma 2 is built on the Gemma 4 architecture, but it has been adapted for embedding rather than generation. The output head is different, the training objective is different and the way you interact with it is entirely different.

Where Embeddings Are Used in Practice

Embeddings are the foundation of many systems you encounter daily, often invisibly. Understanding where they are used helps clarify what EmbeddingGemma 2 is designed for and where it might fit in your own architecture.

Semantic search is the most direct application. Instead of matching keywords, the system retrieves documents whose meaning matches the query. This works across vocabulary differences, handles paraphrasing naturally and supports cross-lingual search when the model has multilingual alignment. Enterprise search, product search and technical documentation search all benefit.

Retrieval-augmented generation is perhaps the most prominent current use case. Before a generative model answers a question, an embedding model retrieves relevant context from a knowledge base. This grounds the response in specific information rather than training data, reduces hallucination and enables up-to-date answers. The quality of the retrieval directly affects the quality of the final response.

Code search is a specialized but important application. Developers use embedding-based search to find functions, classes, or code snippets across large codebases by describing what they need in natural language. EmbeddingGemma 2's improved code performance makes it suitable for this.

Recommendation systems use embeddings to represent items and users. Similar items cluster together, enabling discovery of related products, articles, or media. Collaborative filtering can be combined with content-based embeddings for hybrid recommendations.

Clustering and classification use embeddings as features. Documents with similar embeddings cluster naturally, enabling topic discovery. Embeddings also serve as input to simple classifiers for sentiment analysis, spam detection, or content categorization. The fixed vector format makes this straightforward.

Duplicate detection relies on embeddings to find near-duplicate content across large corpora. Documents or products that are semantically identical but expressed differently end up with similar vectors, enabling deduplication at scale.

Multimodal search is where EmbeddingGemma 2 distinguishes itself. By mapping text, images, audio and video into a shared space, it enables cross-

modal retrieval: searching for images with text queries, finding audio clips that match a description, locating video segments via voice memos. This eliminates the need for separate embedding models for each modality and ensures consistent representation across content types.

The common thread across all these applications is that embeddings transform a qualitative problem about meaning into a quantitative problem about distance. Once you have good embeddings, the rest of the system becomes engineering: indexing, retrieval, evaluation and optimization. The quality of the embeddings sets the ceiling for everything downstream.

Chapter 2: How Transformers Generate Embeddings

Transformer Architecture in Brief

Embedding models like EmbeddingGemma 2 are built on transformer architectures, so understanding how transformers work is essential to understanding how embeddings are produced. The transformer was introduced in the 2017 paper “Attention Is All You Need” and has since become the foundation of virtually all modern language and embedding models.

At its core, a transformer processes sequences of tokens through multiple identical layers. Each layer contains two main components: a multi-head self-attention mechanism and a feed-forward neural network. The model also uses residual connections and layer normalization throughout to maintain stable gradients during training and inference.

The input to a transformer begins as a sequence of tokens. These tokens are produced by a tokenizer that breaks text into subword units. For example, the sentence “embedding models are powerful” might be tokenized into [“embed”, “ding”, “ models“, “ are“, “ powerful“]. Each token is converted into an embedding vector and positional encodings are added to preserve the order information that would otherwise be lost.

The self-attention mechanism is what gives transformers their power. For each token in the sequence, self-attention computes a weighted combination of all tokens’ representations, where the weights reflect how relevant each token is to the current one. This allows the model to capture long-range dependencies. If the sentence contains “the bank account near the river,” self-attention helps the model understand which “bank” refers to which concept by attending to contextual clues.

Multi-head attention runs this process multiple times in parallel with different learned projections, enabling the model to capture different types of relationships simultaneously. One head might focus on syntactic structure,

another on semantic similarity, another on coreference. The outputs are concatenated and projected back to the original dimension.

The feed-forward network applies a non-linear transformation to each token's representation independently. It typically consists of two linear layers with a ReLU or GeLU activation in between, expanding the dimensionality in the middle layer and then projecting back. This allows the model to perform complex feature transformations after the attention has mixed information across the sequence.

Stacking multiple layers allows information to flow and transform progressively. Early layers capture local patterns and basic syntax. Middle layers build more complex representations. Later layers encode high-level semantics and task-specific features. For EmbeddingGemma 2, the exact number of layers depends on the encoder configuration, with the text backbone following the Gemma 4 architecture's layer design.

For an embedding model specifically, the transformer is used as an encoder rather than a decoder. It does not generate tokens autoregressively. Instead, it processes the entire input sequence and produces internal representations that are then converted into a fixed-length embedding vector through pooling or selection operations.

Self-Attention and Semantic Understanding

The reason transformers excel at producing high-quality embeddings lies in how self-attention captures semantic relationships. Unlike earlier architectures that processed text sequentially or with fixed receptive fields, self-attention allows every token to potentially attend to every other token in a single step.

Consider how a transformer handles the phrase “Python programming language.” The token “Python” could refer to a snake or a programming language. Through self-attention, the model attends to the following tokens “programming language,” which disambiguate the meaning. The representation of “Python” after the attention layer encodes the programming context, not just the word itself.

This contextual understanding is what makes transformer-based embeddings superior to static word embeddings. The same word produces different vectors in different contexts and these context-dependent vectors capture

nuanced meaning. When the entire sequence is then pooled into a single embedding, the resulting vector reflects the full semantic content of the input, including how individual words relate to each other.

Self-attention also captures relationships across longer distances in the text. In a paragraph, the first sentence might set up a topic that is referenced in the fifth sentence. A convolutional network with a limited kernel size would miss this connection, but self-attention can link them directly. This is crucial for embedding models that need to represent documents or long queries where important information might be spread across the input.

The multi-head design adds depth to this capability. Different attention heads can specialize in different aspects of the input. Research on transformer interpretability has shown that some heads attend to positional information, others to specific syntactic relationships and others to semantic concepts. The combination of all heads provides a rich representation that pooling operations can then aggregate.

For EmbeddingGemma 2, the self-attention mechanism is inherited from the Gemma 4 architecture. Gemma models use a standard multi-head attention design with learned projections for queries, keys and values. The model's capacity to produce high-quality embeddings across text, code and multiple languages stems from how thoroughly these attention mechanisms have been trained to capture relevant patterns across diverse input types.

Tokenization and Context Windows

Before any embedding computation happens, the input must be tokenized. Tokenization is the process of breaking raw text into discrete units that the model can process. Most modern models, including EmbeddingGemma 2, use subword tokenization with a vocabulary of tens of thousands of units.

Subword tokenization strikes a balance between word-level and character-level tokenization. Common words are represented as single tokens. Rare words are broken into meaningful subword units. The word “unembedding” might be tokenized as [“un”, “embed”, “ding”], each of which appears frequently in other contexts. This keeps vocabulary size manageable while maintaining good coverage.

Tokenization has practical implications for working with embedding models. The context window is measured in tokens, not characters or words.

EmbeddingGemma 2 supports 8,192 tokens. English text averages roughly 3 to 4 tokens per word, so a single input might contain 2,000 to 2,500 words. Technical text with code or special formatting often has more tokens per character due to the tokenizer’s handling of symbols and identifiers.

For multimodal inputs, tokenization works differently for each modality but shares the same context budget. Images are converted to visual tokens through the vision encoder, audio to audio tokens through the audio encoder and these are interleaved with text tokens in the sequence. This is why Google specifies concrete limits: up to 5.5 minutes of audio, 29 images, or 58 video frames in a single input. Each modality consumes tokens from the shared 8,192 budget.

The tokenization process also affects embedding quality. Different tokenizers produce different token boundaries, which can affect how the model processes and represents the input. For code embedding specifically, how the tokenizer handles identifiers, operators and whitespace matters. EmbeddingGemma 2’s tokenizer is designed to handle programming language syntax reasonably well, which contributes to its strong MTEB Code performance.

When preprocessing documents for embedding, it is important to understand how tokenization affects your data. Text that includes URLs, HTML, or other formatting artifacts consumes tokens without adding semantic value. Cleaning and normalizing input before tokenization can improve both efficiency and quality. The exact cleaning strategy depends on your data, but common practices include removing markup, normalizing whitespace and collapsing URLs or technical identifiers.

From Sequence Output to Vector Embedding

The transformer processes the input and produces a sequence of token representations. Each token has its own vector after passing through all the layers. But for most embedding use cases, you need a single vector that represents the entire input, not individual token vectors. Converting the sequence output to a single embedding requires a pooling strategy.

Mean pooling is one of the simplest and most common approaches. It averages all the token vectors in the sequence to produce a single vector. This works well because each token representation has been conditioned on the full context through self-attention, so averaging them captures the overall

meaning of the input. Mean pooling is robust to input length variation and does not favor any particular position in the sequence.

CLS token pooling uses the representation of a special classification token prepended to the input sequence. This token's representation aggregates information from all other tokens through attention. Many BERT-based models use CLS pooling. The question is whether this single token's representation is as effective as averaging all tokens and empirical evidence is mixed. Some models benefit from CLS pooling, others from mean pooling.

EOS token pooling uses the representation of the end-of-sequence token, on the assumption that it has attended to everything that came before. This approach is used by some encoder-decoder models but is less common for dedicated embedding models.

For EmbeddingGemma 2, the recommended approach via sentence-transformers uses mean pooling by default, which has been tuned as part of the model's training and evaluation pipeline. The sentence-transformers library handles pooling automatically, including handling of attention masks so that padding tokens do not contribute to the average.

The pooling operation is not just a technical detail. It affects the quality of the final embeddings. A model can be trained specifically with one pooling strategy in mind and changing it at inference time can degrade performance. This is why using officially supported tooling like sentence-transformers matters: it applies the pooling strategy the model was designed for.

After pooling, the embedding vector is typically L2-normalized, meaning its length is scaled to 1.0. This ensures that cosine similarity between embeddings is equivalent to their dot product, which simplifies computation and improves numerical stability for retrieval operations. EmbeddingGemma 2 produces normalized embeddings and this normalization is an essential part of the pipeline, especially when using truncated vectors from Matryoshka Representation Learning.

Why Transformers Excel at Semantic Encoding

The transformer architecture's success at producing high-quality semantic embeddings is not accidental. Several design choices contribute:

First, the self-attention mechanism captures global context. Every token's representation is conditioned on every other token, allowing the model to

understand how words relate within the full scope of the input. This is essential for disambiguation and for representing inputs where meaning depends on the overall context rather than local patterns.

Second, the layer stacking allows hierarchical representation learning. Lower layers capture local and syntactic patterns, while higher layers build increasingly abstract semantic representations. By the time the sequence reaches the final layer, the token representations encode rich semantic information that pooling operations can effectively aggregate.

Third, the architecture is inherently parallel. Unlike recurrent models that process tokens sequentially and can struggle with very long-range dependencies, transformers process the entire sequence in parallel through attention. This allows them to capture relationships across the full input length without degradation.

Fourth, training at scale on diverse data teaches the model broad semantic patterns. EmbeddingGemma 2 was trained on data from over 100 languages, including code, web text and synthetic examples. This diversity gives it the ability to produce useful embeddings across many domains and languages rather than being narrowly specialized.

Fifth, instruction tuning adds task-specific optimization. By training with task prefixes, the model learns to produce embeddings that are optimized for specific use cases like retrieval, classification, or clustering. This means the same base architecture can produce different types of representations depending on how it is prompted, increasing its flexibility.

The combination of these factors is why transformer-based embedding models like EmbeddingGemma 2 consistently outperform earlier approaches like TF-IDF, word count vectors, or even static embeddings from Word2Vec. They understand context, handle ambiguity, generalize across domains and produce representations that are directly usable for a wide range of semantic tasks.

Chapter 3: The Embedding Pipeline: Pooling, Normalization and Beyond

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Mean Pooling and Token Aggregation

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