Oracle® Database

Oracle AI Vector Search User's Guide

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Preface

Oracle Database AI Vector Search User's Guide provides information about querying semantic and business data with Oracle AI Vector Search.

Audience

This guide is intended for application developers, database administrators, data users, and others who perform the following tasks:

- Implement artificial intelligence (AI) solutions for websites and unstructured or structured data
- Build query applications by using natural language processing and machine learning techniques
- Perform similarity searches on content, such as words, documents, audio tracks, or images

To use this document, you must have a basic familiarity with vector embedding and machine learning concepts, SQL, SQL*Plus, and PL/SQL.

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Conventions

The following text conventions are used in this document:

Convention	Meaning
boldface	Boldface type indicates graphical user interface elements associated with an action, or terms defined in text or the glossary.
italic	Italic type indicates book titles, emphasis, or placeholder variables for which you supply particular values.
`monospace`	Monospace type indicates commands within a paragraph, URLs, code in examples, text that appears on the screen, or text that you enter.

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Overview

Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.

- Overview of Oracle AI Vector Search
  Oracle AI Vector Search is designed for Artificial Intelligence (AI) workloads and allows you to query data based on semantics, rather than keywords.
- Why Use Oracle AI Vector Search?
  One of the biggest benefits of Oracle AI Vector Search is that semantic search on unstructured data can be combined with relational search on business data in one single system.
- Oracle AI Vector Search Workflow
  A typical Oracle AI Vector Search workflow follows the included primary steps.

Overview of Oracle AI Vector Search

Oracle AI Vector Search is designed for Artificial Intelligence (AI) workloads and allows you to query data based on semantics, rather than keywords.

VECTOR Data Type

The `VECTOR` data type is introduced with the release of Oracle Database 23ai, providing the foundation to store vector embeddings alongside business data in the database. Using embedding models, you can transform unstructured data into vector embeddings that can then be used for semantic queries on business data.

See the following basic example of using the `VECTOR` data type in a table definition:

```
CREATE TABLE docs (INT doc_id, CLOB doc_text, VECTOR doc_vector);
```

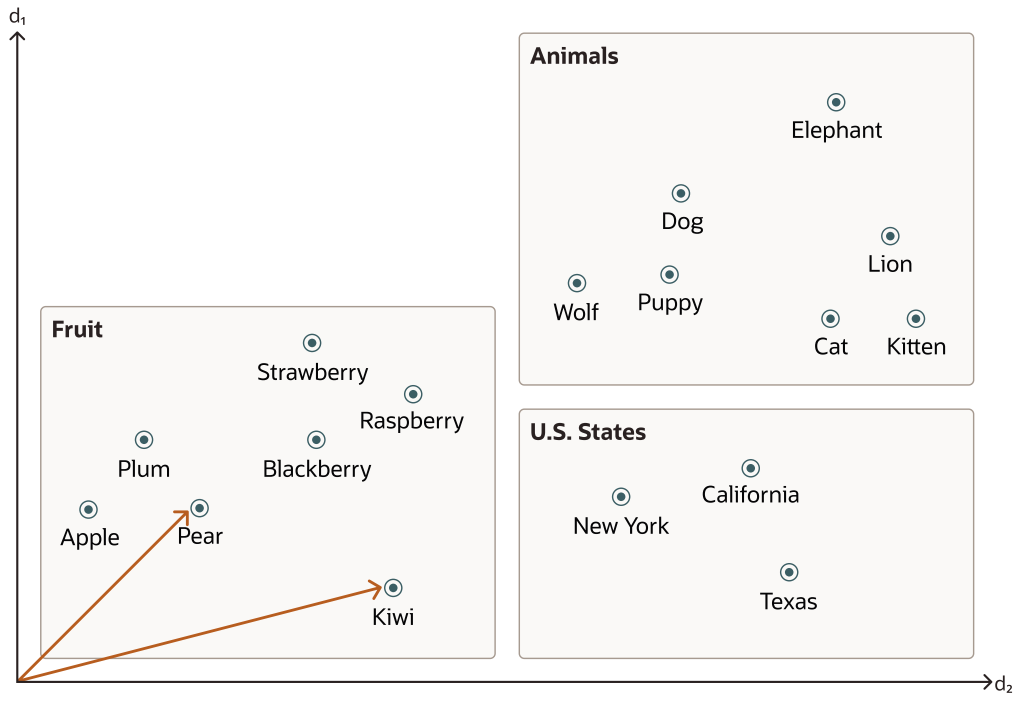
For more information about the `VECTOR` data type and how to use vectors in tables, see Create Tables Using the VECTOR Data Type.

Vector Embeddings

If you've ever used applications such as voice assistants, chatbots, language translators, recommendation systems, anomaly detection, or video search and recognition, you've implicitly used vector embeddings features.

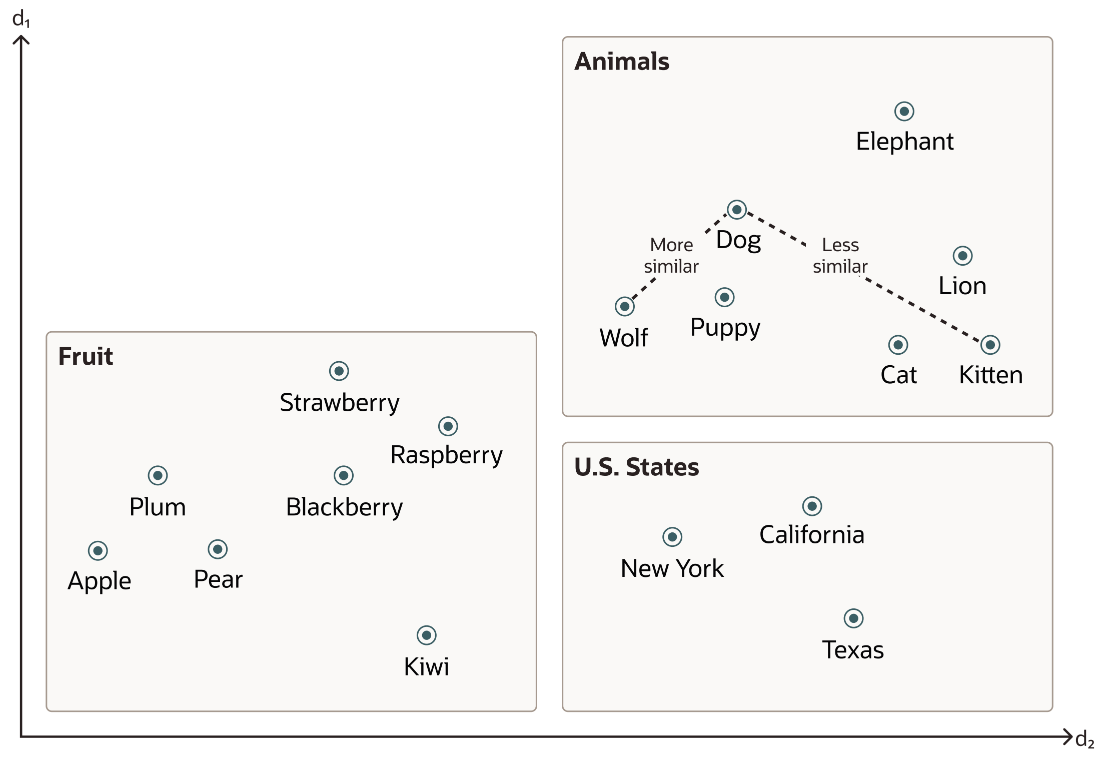
Oracle AI Vector Search stores vector embeddings, which are mathematical vector representations of data points. These vector embeddings describe the semantic meaning behind content such as words, documents, audio tracks, or images. As an example, while doing text based searches, vector search is often considered better than keyword search as vector search is based on the meaning and context behind the words and not the actual words themselves. This vector representation translates semantic similarity of objects, as perceived by humans, into proximity in a mathematical vector space. This vector space usually has multihundreds, if not thousands, of dimensions. Put differently, vector embeddings are a way of representing almost any kind of data, such as text, images, videos, users, or music as points in a multidimensional space where the locations of those points in space, and proximity to others, are semantically meaningful.

This simplified diagram illustrates a vector space where words are encoded as 2-dimensional vectors.



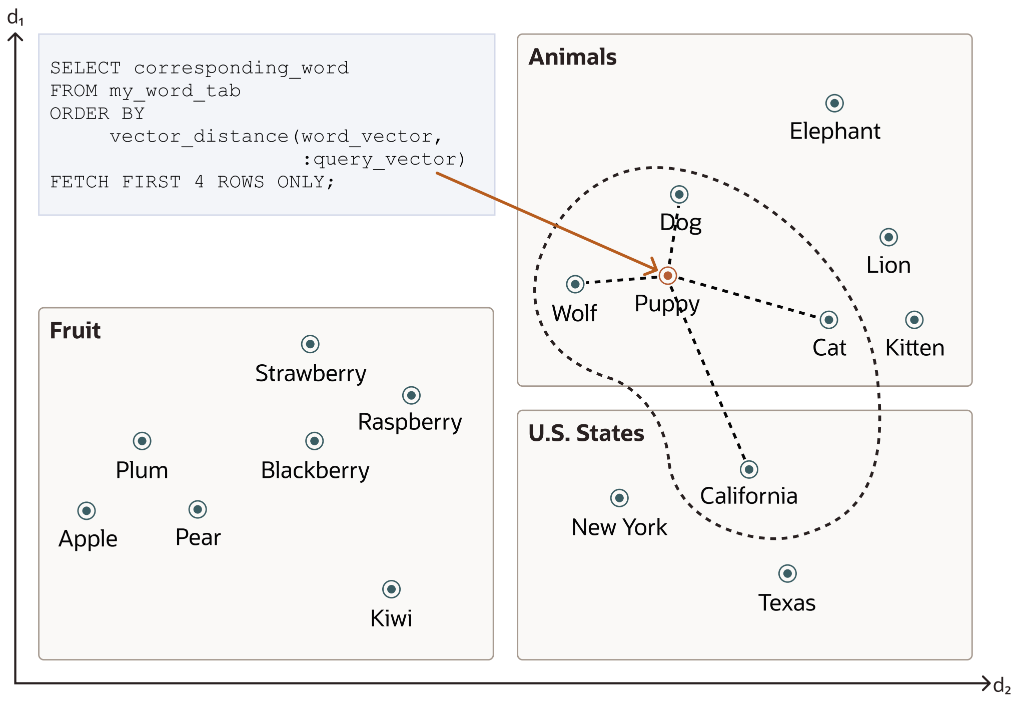
Similarity Search

Searching semantic similarity in a data set is now equivalent to searching nearest neighbors in a vector space instead of using traditional keyword searches using query predicates. As illustrated in the following diagram, the distance between *dog* and *wolf* in this vector space is shorter than the distance between *dog* and *kitten*. In this space, a dog is more similar to a wolf than it is to a kitten. See Perform Exact Similarity Search for more information.



Vector data tends to be unevenly distributed and clustered into groups that are semantically related. Doing a similarity search based on a given query vector is equivalent to retrieving the K-nearest vectors to your query vector in your vector space. Basically, you need to find an ordered list of vectors by ranking them, where the first row in the list is the closest or most similar vector to the query vector, the second row in the list is the second closest vector to the query vector, and so on. When doing a similarity search, the relative order of distances is what really matters rather than the actual distance.

Using the preceding vector space, here is an illustration of a semantic search where your query vector is the one corresponding to the word *Puppy* and you want to identify the four closest words:


```
SELECT corresponding_word
FROM my_word_tab
ORDER BY
     vector_distance(word_vector,
                     :query_vector)
FETCH FIRST 4 ROWS ONLY;
```

Similarity searches tend to get data from one or more clusters depending on the value of the query vector and the fetch size.

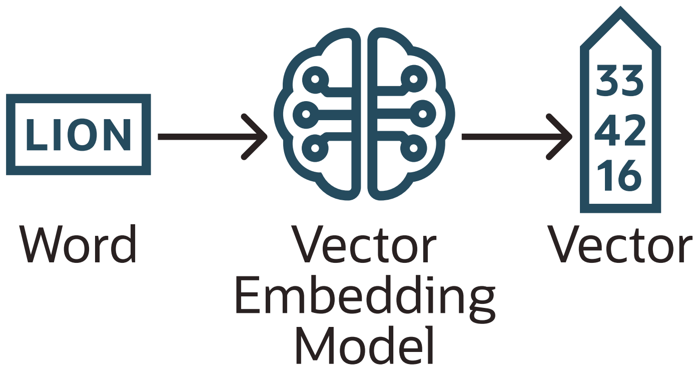
Approximate searches using *vector indexes* can limit the searches to specific clusters, whereas exact searches visit vectors across all clusters. See Use Vector Indexes for more information.

Vector Embedding Models

One way of creating such vector embeddings could be to use someone's domain expertise to quantify a predefined set of features or dimensions such as shape, texture, color, sentiment, and many others, depending on the object type with which you're dealing. However, the efficiency of this method depends on the use case and is not always cost effective.

Instead, vector embeddings are created via neural networks. Most modern vector embeddings use a transformer model, as illustrated by the following diagram, but convolutional neural networks can also be used.

Figure 1-1 Vector Embedding Model



Depending on the type of your data, you can use different pretrained, open-source models to create vector embeddings. For example:

- For textual data, sentence transformers transform words, sentences, or paragraphs into vector embeddings.
- For visual data, you can use Residual Network (ResNet) to generate vector embeddings.
- For audio data, you can use the visual spectrogram representation of the audio data to fall back into the visual data case.

Each model also determines the number of dimensions for your vectors. For example:

- Cohere's embedding model embed-english-v3.0 has 1024 dimensions.
- OpenAI's embedding model text-embedding-3-large has 3072 dimensions.
- Hugging Face's embedding model all-MiniLM-L6-v2 has 384 dimensions

Of course, you can always create your own model that is trained with your own data set.

Import Embedding Models into Oracle Database

Although you can generate vector embeddings outside the Oracle Database using pretrained open-source embeddings models or your own embeddings models, you also have the option to import those models directly into the Oracle Database if they are compatible with the Open Neural Network Exchange (ONNX) standard. Oracle Database implements an ONNX runtime directly within the database. This allows you to generate vector embeddings directly within the Oracle Database using SQL. See Generate Vector Embeddings for more information.

Why Use Oracle AI Vector Search?

One of the biggest benefits of Oracle AI Vector Search is that semantic search on unstructured data can be combined with relational search on business data in one single system.

This is not only powerful but also significantly more effective because you don't need to add a specialized vector database, eliminating the pain of data fragmentation between multiple systems.

For example, suppose you use an application that allows you to find a house that is similar to a picture you took of one you like that is located in your preferred area for a certain budget. Finding a good match in this case requires combining a semantic picture search with searches on business data.

With Oracle AI Vector Search, you can create the following table:

```
CREATE TABLE house_for_sale (house_id     NUMBER,
                             price        NUMBER,
                             city         VARCHAR2(400),
                             house_photo  BLOB,
                             house_vector VECTOR);
```

The following sections of this guide describe in detail the meaning of the `VECTOR` data type and how to load data in this column data type.

With that table, you can run the following query to answer your basic question:

```
SELECT house_photo, city, price
FROM   house_for_sale
WHERE  price <= :input_price AND
       city  = :input_city
ORDER BY VECTOR_DISTANCE(house_vector, :input_vector);
```

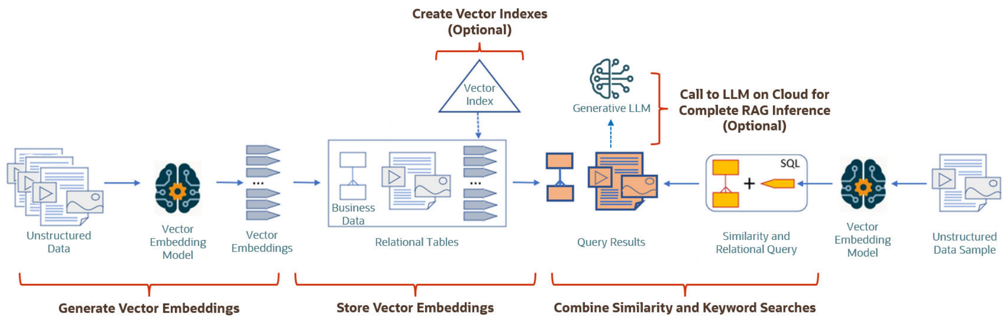
Later sections of this guide describe in detail the meaning of the `VECTOR_DISTANCE` function. This query is just to show you how simple it is to combine a vector embedding similarity search with relation predicates.

Oracle AI Vector Search Workflow

A typical Oracle AI Vector Search workflow follows the included primary steps.

This is illustrated in the following diagram:

Figure 1-2 Oracle AI Vector Search Use Case Flowchart



To understand the diagram, consider this high level workflow description. Vector embeddings are generated by passing unstructured data through an embedding model. Vector embeddings can then be stored alongside business data in relational tables and vector indexes can optionally be created. Once you have the vector representations of your unstructured data stored in your database table(s), a sample of unstructured data can be passed through the embedding model to create a query vector. With the query vector, you can perform similarity searches against the vectors that are already stored in the database, in combination with relational queries if desired. To form a complete Retrieval Augmented Generation (RAG) pipeline, it is also possible to make a call to a generative Large Language Model (LLM) as part of the query step.

Primary workflow steps:

1. **Generate Vector Embeddings from Your Unstructured Data**
   You can perform this step either outside or within Oracle Database. For more information, see Generate Vector Embeddings.
2. **Store Vector Embeddings, Unstructured Data, and Relational Business Data in Oracle Database**

You store the resulting vector embeddings and associated unstructured data with your relational business data in Oracle Database. For more information, see Store Vector Embeddings.

3. **Create Vector Indexes**
   You may want to create vector indexes on your vector embeddings. This is beneficial for running similarity searches over huge vector spaces. For more information, see Create Vector Indexes.
4. **Query Data with Similarity Searches**
   You can then use Oracle AI Vector Search native SQL operations to combine similarity with relational searches to retrieve relevant data. For more information, see Query Data with Similarity Searches.
5. **Generate a Prompt and Send it to an LLM for a Full RAG Inference**
   You can use the similarity search results to generate a prompt and send it to your generative LLM of choice for a complete RAG pipeline. For more information, see Work with Retrieval Augmented Generation.

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Get Started

To get started, review the steps for the different tasks that you can do with Oracle AI Vector Search.

- SQL Quick Start
  A set of SQL commands is provided to run a particular scenario that will help you understand Oracle AI Vector Search capabilities.

SQL Quick Start

A set of SQL commands is provided to run a particular scenario that will help you understand Oracle AI Vector Search capabilities.

This quick start scenario introduces you to the `VECTOR` data type, which represents the semantic meaning behind your unstructured data. You will also use Vector Search SQL operators, allowing you to perform a similarity search to find vectors (and thereby content) that are similar to each other. Vector indexes are also created to help you accelerate similarity searches in an approximate manner. See Overview of Oracle AI Vector Search for more introductory information if needed.

The script chunks two Oracle Database Documentation books, assigns them corresponding vector embeddings, and shows you some similarity searches using vector indexes.

To run this script you need three files similar to the following:

- `my_embedding_model.onnx`, which is an ONNX export of the corresponding embedding model. To create such a file, see Convert Pretrained Models to ONNX Format.
- `database-concepts23ai.pdf`, which is the PDF file for Oracle Database 23ai Oracle Database Concepts manual.
- `oracle-ai-vector-search-users-guide.pdf`, which is the PDF file for this guide that you are reading.

> **Note:**
>
> You can use other PDF files instead of the ones listed here. If you prefer, you can use another model of your choice as long as you can generate it as an `.onnx` file.

Let's start.

1. Copy the files to your local directory.

There is no script and you can use `scp`. For example, to copy the three files to a directory on your server. You can call that directory `/my_local_dir`.

```
scp my_embedding_model.onnx /my_local_dir
scp database-concepts23ai.pdf /my_local_dir
scp oracle-ai-vector-search-users-guide.pdf /my_local_dir
```

2. Create storage, user, and privileges.

   Here you create a new tablespace and a new user. You grant that user the `DB_DEVELOPER_ROLE` and create an Oracle directory to point to the PDF files. You grant the new user the possibility to read and write from/to that directory.

```
sqlplus / as sysdba

CREATE TABLESPACE tbs1
DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
EXTENT MANAGEMENT LOCAL
SEGMENT SPACE MANAGEMENT AUTO;

drop user vector cascade;

create user vector identified by vector DEFAULT TABLESPACE tbs1
quota unlimited on tbs1;

grant DB_DEVELOPER_ROLE to vector;

create or replace directory VEC_DUMP as '/my_local_dir/';

grant read, write on directory vec_dump to vector;
```

3. Load your embedding model into the Oracle Database.

   Using the `DBMS_VECTOR` package, load your embedding model into the Oracle Database. You must specify the directory where you stored your model in ONNX format as well as describe what type of model it is and how you want to use it.

   For more information about downloading pretrained embedding models, converting them into ONNX format, and importing the ONNX file into Oracle Database, see Import Pretrained Models in ONNX Format for Vector Generation Within the Database.

```
connect vector/<vector user password>@<pdb instance network name>

exec dbms_vector.drop_onnx_model(model_name => 'doc_model', force
=> true);

EXECUTE dbms_vector.load_onnx_model('VEC_DUMP',
'my_embedding_model.onnx', 'doc_model', JSON('{"function" :
"embedding", "embeddingOutput" : "embedding" , "input": {"input":
["DATA"]}}'));
```

4. Create a relational table to store books in the PDF format.

You now create a table containing all the books you want to chunk and vectorize. You associate each new book with an ID and a pointer to your local directory where the books are stored.

```
drop table documentation_tab purge;
create table documentation_tab (id number, data blob);
insert into documentation_tab values(1, to_blob(bfilename('VEC_DUMP',
'database-concepts23ai.pdf')));
insert into documentation_tab values(2, to_blob(bfilename('VEC_DUMP',
'oracle-ai-vector-search-users-guide.pdf')));
commit;
select dbms_lob.getlength(data) from documentation_tab;
```

5. Create a relational table to store unstructured data chunks and associated vector embeddings using `my_embedding_model.onnx`.

   You start by creating the table structure using the `VECTOR` data type. For more information about declaring a table's column as a `VECTOR` data type, see Create Tables Using the VECTOR Data Type .

   The `INSERT` statement reads each PDF file from `DOCUMENTATION_TAB`, transforms each PDF file into text, chunks each resulting text, then finally generates corresponding vector embeddings on each chunk that is created. All that is done in one single `INSERT SELECT` statement.

   Here you choose to use Vector Utility PL/SQL package `DBMS_VECTOR_CHAIN` to convert, chunk, and vectorize your unstructured data in one end-to-end pipeline. Vector Utility PL/SQL functions are intended to be a set of chainable stages (using table functions) through which you pass your input data to transform into a different representation. In this case, from PDF to text to chunks to vectors. For more information about using chainable utility functions in the `DBMS_VECTOR_CHAIN` package, see About Chainable Utility Functions and Common Use Cases.

```
drop table doc_chunks purge;
create table doc_chunks (doc_id number, chunk_id number, chunk_data
varchar2(4000), chunk_embedding vector);

insert into doc_chunks
select dt.id doc_id, et.embed_id chunk_id, et.embed_data chunk_data,
to_vector(et.embed_vector) chunk_embedding
from
    documentation_tab dt,
    dbms_vector_chain.utl_to_embeddings(

dbms_vector_chain.utl_to_chunks(dbms_vector_chain.utl_to_text(dt.data),
json('{"normalize":"all"}')),
       json('{"provider":"database", "model":"doc_model"}')) t,
    JSON_TABLE(t.column_value, '$[*]' COLUMNS (embed_id NUMBER PATH
'$.embed_id', embed_data VARCHAR2(4000) PATH '$.embed_data', embed_vector
CLOB PATH '$.embed_vector')) et;

commit;
```

See Also:

- *Oracle Database JSON Developer’s Guide* for information about the `JSON_TABLE` function, which supports the `VECTOR` data type

6. Generate a query vector for use in a similarity search.

   For a similarity search you will need query vectors. Here you enter your query text and generate an associated vector embedding.

   For example, you can use the following text: 'different methods of backup and recovery'. You use the `VECTOR_EMBEDDING` SQL function to generate the vector embeddings from the input text. The function takes an embedding model name and a text string to generate the corresponding vector. Note that you can generate vector embeddings outside of the database using your favorite tools. For more information about using the `VECTOR_EMBEDDING` SQL function, see Use SQL Functions to Generate Embeddings.

   In SQL*Plus, use the following code:

```
ACCEPT text_input CHAR PROMPT 'Enter text: '
VARIABLE text_variable VARCHAR2(1000)
VARIABLE query_vector VECTOR
BEGIN
  :text_variable := '&text_input';
  SELECT vector_embedding(doc_model using :text_variable as data)
into :query_vector;
END;
/

PRINT query_vector
```

   In SQLCL, use the following code:

```
DEFINE text_input = '&text'

SELECT '&text_input';

VARIABLE text_variable VARCHAR2(1000)
VARIABLE query_vector CLOB
BEGIN
  :text_variable := '&text_input';
  SELECT vector_embedding(doc_model using :text_variable as data)
into :query_vector;
END;
/

PRINT query_vector
```

7. Run a similarity search to find, within your books, the first four most relevant chunks that talk about backup and recovery.

Using the generated query vector, you search similar chunks in the `DOC_CHUNKS` table. For this, you use the `VECTOR_DISTANCE` SQL function and the `FETCH` SQL clause to retrieve the most similar chunks.

For more information about the `VECTOR_DISTANCE` SQL function, see Vector Distance Functions.

For more information about exact similarity search, see Perform Exact Similarity Search.

```
SELECT doc_id, chunk_id, chunk_data
FROM doc_chunks
ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
FETCH FIRST 4 ROWS ONLY;
```

You can also add a `WHERE` clause to further filter your search, for instance if you only want to look at one particular book.

```
SELECT doc_id, chunk_id, chunk_data
FROM doc_chunks
WHERE doc_id=1
ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
FETCH FIRST 4 ROWS ONLY;
```

8. Use the `EXPLAIN PLAN` command to determine how the optimizer resolves this query.

```
EXPLAIN PLAN FOR
SELECT doc_id, chunk_id, chunk_data
FROM doc_chunks
ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
FETCH FIRST 4 ROWS ONLY;

select plan_table_output from
table(dbms_xplan.display('plan_table',null,'all'));


PLAN_TABLE_OUTPUT
--------------------------------------------------------------------------
----
Plan hash value: 1651750914
--------------------------------------------------------------------------
-----------------------
| Id  | Operation              | Name          | Rows  | Bytes |TempSpc|
Cost (%CPU)| Time     |
--------------------------------------------------------------------------
-----------------------
|   0 | SELECT STATEMENT       |               |     4 |   104 |
|   549   (3)| 00:00:01 |
|*  1 |  COUNT STOPKEY         |               |       |       |
|            |          |
|   2 |   VIEW                 |               |  5014 |   127K|
|   549   (3)| 00:00:01 |
|*  3 |    SORT ORDER BY STOPKEY|              |  5014 |   156K|
232K|   549   (3)| 00:00:01 |
|   4 |     TABLE ACCESS FULL  | DOC_CHUNKS    |  5014 |   156K|
|   480   (3)| 00:00:01 |
--------------------------------------------------------------------
-----------------------------
```

9. Run a multi-vector similarity search to find, within your books, the first four most relevant chunks in the first two most relevant books.

   Here you keep using the same query vector as previously used.

   For more information about performing multi-vector similarity search, see Perform Multi-Vector Similarity Search.

   ```
   SELECT doc_id, chunk_id, chunk_data
   FROM doc_chunks
   ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
   FETCH FIRST 2 PARTITIONS BY doc_id, 4 ROWS ONLY;
   ```

10. Create an In-Memory Neighbor Graph Vector Index on the vector embeddings that you created.

    When dealing with huge vector embedding spaces, you may want to create vector indexes to accelerate your similarity searches. Instead of scanning each and every vector embedding in your table, a vector index uses heuristics to reduce the search space to accelerate the similarity search. This is called approximate similarity search.

    For more information about creating vector indexes, see Create Vector Indexes.

    Note:

    You must have explicit `SELECT` privilege to select from the `VECSYS.VECTOR$INDEX` table, which gives you detailed information about your vector indexes.

    ```
    create vector index docs_hnsw_idx on doc_chunks(chunk_embedding)
    organization inmemory neighbor graph
    distance COSINE
    with target accuracy 95;

    SELECT INDEX_NAME, INDEX_TYPE, INDEX_SUBTYPE
    FROM USER_INDEXES;
    INDEX_NAME      INDEX_TYPE  INDEX_SUBTYPE
    -------------- ----------- -----------------------------
    DOCS_HNSW_IDX   VECTOR      INMEMORY_NEIGHBOR_GRAPH_HNSW

    ...

    SELECT JSON_SERIALIZE(IDX_PARAMS returning varchar2 PRETTY)
    FROM VECSYS.VECTOR$INDEX where IDX_NAME = 'DOCS_HNSW_IDX';
    JSON_SERIALIZE(IDX_PARAMSRETURNINGVARCHAR2PRETTY)
    ________________________________________________________________
    {
      "type" : "HNSW",
      "num_neighbors" : 32,
      "efConstruction" : 300,
    ```

```
  "distance" : "COSINE",
  "accuracy" : 95,
  "vector_type" : "FLOAT32",
  "vector_dimension" : 384,
  "degree_of_parallelism" : 1,
  "pdb_id" : 3,
  "indexed_col" : "CHUNK_EMBEDDING"
}
```

11. Determine the memory allocation in the vector memory area.

    To get an idea about the size of your In-Memory Neighbor Graph Vector Index in memory, you can use the `V$VECTOR_MEMORY_POOL` view. See Size the Vector Pool for more information about sizing the vector pool to allow for vector index creation and maintenance.

    > **Note:**
    >
    > You must have explicit `SELECT` privilege to select from the `V$VECTOR_MEMORY_POOL` view, which gives you detailed information about the vector pool.

    ```
    select CON_ID, POOL, ALLOC_BYTES/1024/1024 as ALLOC_BYTES_MB,
    USED_BYTES/1024/1024 as USED_BYTES_MB
    from V$VECTOR_MEMORY_POOL order by 1,2;
    ```

12. Run an approximate similarity search to identify, within your books, the first four most relevant chunks.

    Using the previously generated query vector, you search chunks in the `DOC_CHUNKS` table that are similar to your query vector. For this, you use the `VECTOR_DISTANCE` function and the `FETCH APPROX` SQL clause to retrieve the most similar chunks using your vector index.

    For more information about approximate similarity search, see Perform Approximate Similarity Search Using Vector Indexes.

    ```
    SELECT doc_id, chunk_id, chunk_data
    FROM doc_chunks
    ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
    FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;
    ```

    You can also add a `WHERE` clause to further filter your search, for instance if you only want to look at one particular book.

    ```
    SELECT doc_id, chunk_id, chunk_data
    FROM doc_chunks
    WHERE doc_id=1
    ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
    FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;
    ```

13. Use the `EXPLAIN PLAN` command to determine how the optimizer resolves this query.

See **Optimizer Plans for Vector Indexes** for more information about how the Oracle Database optimizer uses vector indexes to run your approximate similarity searches.

```
EXPLAIN PLAN FOR
SELECT doc_id, chunk_id, chunk_data
FROM doc_chunks
ORDER BY vector_distance(chunk_embedding , :query_vector, COSINE)
FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;

select plan_table_output from
table(dbms_xplan.display('plan_table',null,'all'));


PLAN_TABLE_OUTPUT
--------------------------------------------------------------------
------------
Plan hash value: 2946813851
--------------------------------------------------------------------
------------------------------------
| Id  | Operation                     | Name           | Rows  |
Bytes |TempSpc| Cost (%CPU)| Time     |
--------------------------------------------------------------------
------------------------------------
|   0 | SELECT STATEMENT              |                |     4 |
104 |       |  12083  (2)| 00:00:01 |
|*  1 |  COUNT STOPKEY                |                |
|       |       |             |          |
|   2 |   VIEW                        |                |  5014 |
127K|       |  12083  (2)| 00:00:01 |
|*  3 |    SORT ORDER BY STOPKEY      |                |  5014 |
19M|    39M|  12083  (2)| 00:00:01 |
|   4 |     TABLE ACCESS BY INDEX ROWID| DOC_CHUNKS     |  5014 |
19M|       |     1    (0)| 00:00:01 |
|   5 |      VECTOR INDEX HNSW SCAN   | DOCS_HNSW_IDX |  5014 |
19M|       |     1    (0)| 00:00:01 |
--------------------------------------------------------------------
------------------------------------
```

14. Determine your vector index performance for your approximate similarity searches.

    The index accuracy reporting feature allows you to determine the accuracy of your vector indexes. After a vector index is created, you may be interested to know how accurate your approximate vector searches are.

    The `DBMS_VECTOR.INDEX_ACCURACY_QUERY` PL/SQL procedure provides an accuracy report for a top-K index search for a specific query vector and a specific target accuracy. In this case you keep using the query vector generated previously. For more information about index accuracy reporting, see Index Accuracy Report.

```
SET SERVEROUTPUT ON
declare
    report varchar2(128);
begin
```

```
    report := dbms_vector.index_accuracy_query(
        OWNER_NAME => 'VECTOR',
        INDEX_NAME => 'DOCS_HNSW_IDX',
        qv => :query_vector,
        top_K => 10,
        target_accuracy => 90 );
    dbms_output.put_line(report);
end;
/
```

The report looks like the following: Accuracy achieved (100%) is 10% higher than the Target Accuracy requested (90%).

3

Generate Vector Embeddings

You must generate vector embeddings from your unstructured data either outside or within Oracle Database.

To get vector embeddings, you can either use ONNX embedding machine learning models or access third-party REST APIs.

- Import Pretrained Models in ONNX Format for Vector Generation Within the Database
  You can download pretrained embedding machine learning models, convert them into ONNX format if they are not already in ONNX format, import the ONNX format models into Oracle Database, and generate vector embeddings from your data within the database.
- Generate Vector Embeddings Using Vector Utilities Leveraging Third-Party REST APIs
  Oracle AI Vector Search offers vector utilities (SQL and PL/SQL tools) to automatically generate vector embeddings from your unstructured data.
- Vector Generation Examples
  Review these examples to see how you can generate vectors within and outside the database.

Import Pretrained Models in ONNX Format for Vector Generation Within the Database

You can download pretrained embedding machine learning models, convert them into ONNX format if they are not already in ONNX format, import the ONNX format models into Oracle Database, and generate vector embeddings from your data within the database.

- Import ONNX Models and Generate Embeddings
  Learn to import a pretrained embedding model that is in ONNX format and generate vector embeddings.
- Convert Pretrained Models to ONNX Format
  OML4Py enables the use of text transformers from Hugging Face by converting them into ONNX format models. OML4Py also adds the necessary tokenization and post-processing. The resulting ONNX pipeline is then imported into the database and can be used to generate embeddings for AI Vector Search.

Import ONNX Models and Generate Embeddings

Learn to import a pretrained embedding model that is in ONNX format and generate vector embeddings.

Follow the steps below to import a pertained ONNX formatted embedding model into the Oracle Database.

Prepare Your Data Dump Directory

Prepare your data dump directory and provide the necessary access and privileges to `dmuser`.

1. Choose from:
   a. If you already have a pretrained ONNX embedding model, store it in your working folder.
   b. If you do not have pretrained embedding model in ONNX format, perform the steps listed in Convert Pretrained Models to ONNX Format.
2. Login to SQL*Plus as `SYSDBA` in your PDB.

   ```
   CONN sys/<password>@pdb as sysdba;
   ```

3. Grant the `DB_DEVELOPER_ROLE` to `dmuser`.

   ```
   GRANT DB_DEVELOPER_ROLE TO dmuser identified by <password>;
   ```

4. Grant `CREATE MINING MODEL` privilege to `dmuser`.

   ```
   GRANT create mining model TO dmuser;
   ```

5. Set your working folder as the data dump directory (`DM_DUMP`) to load the ONNX embedding model.

   ```
   CREATE OR REPLACE DIRECTORY DM_DUMP as '<work directory path>';
   ```

6. Grant `READ` permissions on the `DM_DUMP` directory to `dmuser`.

   ```
   GRANT READ ON DIRECTORY dm_dump TO dmuser;
   ```

7. Grant `WRITE` permissions on the `DM_DUMP` directory to `dmuser`.

   ```
   GRANT WRITE ON DIRECTORY dm_dump TO dmuser;
   ```

8. Drop the model if it already exits.

   ```
   exec DBMS_VECTOR.DROP_ONNX_MODEL(model_name => 'doc_model', force
   => true);
   ```

Import ONNX Model Into the Database

You created a data dump directory and now you load the ONNX model into the Database. Use the `DBMS_VECTOR.LOAD_ONNX_MODEL` procedure to load the model. The `DBMS_VECTOR.LOAD_ONNX_MODEL` procedure facilitates the process of importing ONNX format model into the Oracle Database. In this example, the procedure loads an ONNX model file, named `my_embedding_model.onnx` from the `DM_DUMP` directory, into the Database as `doc_model`, specifying its use for embedding tasks.

1. Connect as `dmuser`.

   ```
   CONN dmuser/<password>@<pdbname>;
   ```

2. Load the ONNX model into the Database.

   If the ONNX model to be imported already includes an output tensor named `embeddingOutput` and an input string tensor named `data`, JSON metadata is unnecessary. Embedding models converted from OML4Py follow this convention and can be imported without the JSON metadata.

   ```
   EXECUTE DBMS_VECTOR.LOAD_ONNX_MODEL(
     'DM_DUMP',
    'my_embedding_model.onnx',
    'doc_model');
   ```

   Alternately, you can load the ONNX embedding model by specifying the JSON metadata.

```
EXECUTE DBMS_VECTOR.LOAD_ONNX_MODEL(
     'DM_DUMP',
     'my_embedding_model.onnx',
     'doc_model',
     JSON('{"function" : "embedding", "embeddingOutput" : "embedding", "input": {"input":
["DATA"]}}'));
```

The procedure `LOAD_ONNX_MODEL` declares these parameters:

- `DM_DUMP`: specifies the directory name of the data dump.

  > **Note:**
  >
  > Ensure that the `DM_DUMP` directory is defined.

- `my_embedding_model`: is a `VARCHAR2` type parameter that specifies the name of the ONNX model.
- `doc_model`: This parameter is a user-specified name under which the model is stored in the Oracle Database.
- The JSON metadata associated with the ONNX model is declared as:

  `"function" : "embedding"`: Indicates the function name for text embedding model.

  `"embeddingOutput" : "embedding"`: Specifies the output variable which contains the embedding results.

- `"input": {"input": ["DATA"]}`: Specifies a JSON object (`"input"`) that describes the input expected by the model. It specifies that there is an input named `"input"`, and its value should be an array with one element, `"DATA"`. This indicates that the model expects a single string input to generate embeddings.

See LOAD_ONNX_MODEL Procedure to learn about the PL/SQL procedure.

Query Model Statistics

You can view model attributes and learn about the model by querying machine learning dictionary views and model detail views.

> **Note:**
>
> *DOC_MODEL* is the user-specified name of the embedding text model.

1. Query `USER_MINING_MODEL_ATTRIBUTES` view.

   ```
   SELECT model_name, attribute_name, attribute_type, data_type,
   vector_info
   FROM user_mining_model_attributes
   WHERE model_name = 'DOC_MODEL'
   ORDER BY ATTRIBUTE_NAME;
   ```

   To learn about `USER_MINING_MODEL_ATTRIBUTES` view, see USER_MINING_MODEL_ATTRIBUTES.

2. Query `USER_MINING_MODELS` view.

   ```
   SELECT MODEL_NAME, MINING_FUNCTION, ALGORITHM,
   ALGORITHM_TYPE, MODEL_SIZE
   FROM user_mining_models
   WHERE model_name = 'DOC_MODEL'
   ORDER BY MODEL_NAME;
   ```

   To learn about `USER_MINING_MODELS` view, see USER_MINING_MODELS.

3. Check model statistics by viewing the model detail views. Query the `DM$VM`*`DOC_MODEL`* view.

   ```
   SELECT * FROM DM$VMDOC_MODEL ORDER BY NAME;
   ```

   To learn about model details views for ONNX embedding models, see Model Details Views for ONNX Models.

4. Query the `DM$VP`*`DOC_MODEL`* model detail view.

   ```
   SELECT * FROM DM$VPDOC_MODEL ORDER BY NAME;
   ```

5. Query the `DM$VJ`*`DOC_MODEL`* model detail view.

   ```
   SELECT * FROM DM$VJDOC_MODEL;
   ```

Generate Embeddings

Apply the model and generate vector embeddings for your input. Here, the input is *hello*.

Generate vector embeddings using the `VECTOR_EMBEDDING` function.

```
SELECT TO_VECTOR(VECTOR_EMBEDDING(doc_model USING 'hello' as data)) AS
embedding;
```

To learn about the `VECTOR_EMBEDDING` SQL function, see VECTOR_EMBEDDING. You can use the `UTL_TO_EMBEDDING` function in the `DBMS_VECTOR_CHAIN` PL/SQL package to generate vector embeddings generically through REST endpoints. To explore these functions, see the example Convert Text String to Embedding.

Example: Importing a Pretrained ONNX Model to Oracle Database

The following presents a comprehensive step-by-step example of importing ONNX embedding and generating vector embeddings.

```
conn sys/<password>@pdb as sysdba
grant db_developer_role to dmuser identified by dmuser;
grant create mining model to dmuser;

create or replace directory DM_DUMP as '<work directory path>';
grant read on directory dm_dump to dmuser;
grant write on directory dm_dump to dmuser;
>conn dmuser/<password>@<pdbname>;

-- Drop the model if it exits
exec DBMS_VECTOR.DROP_ONNX_MODEL(model_name => 'doc_model', force => true);

-- Load Model
EXECUTE DBMS_VECTOR.LOAD_ONNX_MODEL(
    'DM_DUMP',
    'my_embedding_model.onnx',
    'doc_model',
    JSON('{"function" : "embedding", "embeddingOutput" : "embedding"}'));
/

--check the attributes view
set linesize 120
col model_name format a20
col algorithm_name format a20
col algorithm format a20
col attribute_name format a20
col attribute_type format a20
col data_type format a20

SQL> SELECT model_name, attribute_name, attribute_type, data_type,
vector_info
FROM user_mining_model_attributes
WHERE model_name = 'DOC_MODEL'
ORDER BY ATTRIBUTE_NAME;


OUTPUT:

MODEL_NAME           ATTRIBUTE_NAME       ATTRIBUTE_TYPE       DATA_TYPE
```

```
VECTOR_INFO
-------------------- -------------------- --------------------
---------- ---------------
DOC_MODEL                INPUT_STRING         TEXT
VARCHAR2
DOC_MODEL                ORA$ONNXTARGET       VECTOR
VECTOR     VECTOR(128,FLOA

   T32)



SQL> SELECT MODEL_NAME, MINING_FUNCTION, ALGORITHM,
ALGORITHM_TYPE, MODEL_SIZE
FROM user_mining_models
WHERE model_name = 'DOC_MODEL'
ORDER BY MODEL_NAME;

OUTPUT:
MODEL_NAME           MINING_FUNCTION
ALGORITHM            ALGORITHM_ MODEL_SIZE
-------------------- ------------------------------
-------------------- ---------- ----------
DOC_MODEL                EMBEDDING
ONNX                 NATIVE       17762137



SQL> select * from DM$VMDOC_MODEL ORDER BY NAME;

OUTPUT:
NAME                                      VALUE
----------------------------------------
----------------------------------------
Graph Description                         Graph combining g_8_torch_jit
and torch_

                                          jit
                                          g_8_torch_jit



                                          torch_jit



Graph Name                                g_8_torch_jit_torch_jit
Input[0]                                  input:string[1]
Output[0]                                 embedding:float32[?,128]
Producer Name                             onnx.compose.merge_models
Version                                   1

6 rows selected.


SQL> select * from DM$VPDOC_MODEL ORDER BY NAME;
```

```
OUTPUT:
NAME                                     VALUE
----------------------------------------
----------------------------------------
batching                                 False
embeddingOutput                          embedding


SQL> select * from DM$VJDOC_MODEL;

OUTPUT:
METADATA
-----------------------------------------------------------------------------
---
{"function":"embedding","embeddingOutput":"embedding","input":{"input":
["DATA"]}}



--apply the model
SQL> SELECT TO_VECTOR(VECTOR_EMBEDDING(doc_model USING 'hello' as data)) AS
embedding;

-----------------------------------------------------------------------------
---
[-9.76553112E-002,-9.89954844E-002,7.69771636E-003,-4.16760892E-003,-9.693056
34E-002,
-3.01141385E-002,-2.63396613E-002,-2.98553891E-002,5.96499592E-002,4.13885899
E-002,
5.32859489E-002,6.57707453E-002,-1.47056757E-002,-4.18472625E-002,4.1588001E-
002,
-2.86354572E-002,-7.56499246E-002,-4.16395674E-003,-1.52879998E-001,6.6001057
6E-002,
-3.9013084E-002,3.15719917E-002,1.2428958E-002,-2.47651711E-002,-1.16851285E-
001,
-7.82847106E-002,3.34323719E-002,8.03267583E-002,1.70483496E-002,-5.42407483E
-002,
6.54291287E-002,-4.81935125E-003,6.11041225E-002,6.64106477E-003,-5.47
```

Oracle AI Vector Search SQL Scenario

To learn how you can chunk *database-concepts23ai.pdf* and *oracle-ai-vector-search-users-guide.pdf*, generate vector embeddings, and perform similarity search using vector indexes, see Quick Start SQL.

- Alternate Method to Import ONNX Models
  Use the `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` procedure to import the model and declare the input name. The following procedure uses a PL/SQL helper block that facilitates the process of importing ONNX format model into the Oracle Database. The function reads the model file from the server's file system and imports it into the Database.

Alternate Method to Import ONNX Models

Use the `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` procedure to import the model and declare the input name. The following procedure uses a PL/SQL helper block that facilitates the process of importing ONNX format model into the Oracle Database. The function reads the model file from the server's file system and imports it into the Database.

Perform the following steps to import ONNX model into the Database using `DBMS_DATA_MINING` PL/SQL package.

- Connect as `dmuser`.

  ```
  CONN dmuser/<password>@<pdbname>;
  ```

- Run the following helper PL/SQL block:

  ```
  DECLARE
      m_blob BLOB default empty_blob();
      m_src_loc BFILE ;
      BEGIN
      DBMS_LOB.createtemporary (m_blob, FALSE);
      m_src_loc := BFILENAME('DM_DUMP', 'my_embedding_model.onnx');
      DBMS_LOB.fileopen (m_src_loc, DBMS_LOB.file_readonly);
      DBMS_LOB.loadfromfile (m_blob, m_src_loc, DBMS_LOB.getlength
  (m_src_loc));
      DBMS_LOB.CLOSE(m_src_loc);
      DBMS_DATA_MINING.import_onnx_model ('doc_model', m_blob,
  JSON('{"function" : "embedding", "embeddingOutput" : "embedding",
  "input": {"input": ["DATA"]}}'));
      DBMS_LOB.freetemporary (m_blob);
      END;
      /
  ```

  The code sets up a `BLOB` object and a `BFILE` locator, creates a temporary `BLOB` for storing the `my_embedding_model.onnx` file from the `DM_DUMP` directory, and reads its contents into the `BLOB`. It then closes the file and uses the content to import an ONNX model into the database with specified metadata, before releasing the temporary `BLOB` resources.

The schema of the `IMPORT_ONNX_MODEL` procedure is as follows: `DBMS_DATA_MINING.IMPORT_ONNX_MODEL(model_data, model_name, metadata)`. This procedure loads `IMPORT_ONNX_MODEL` from the `DBMS_DATA_MINING` package to import the ONNX model into the Database using the name provided in `model_name`, the BLOB content in `m_blob`, and the associated `metadata`.

- `doc_model`: This parameter is a user-specified name under which the imported model is stored in the Oracle Database.
- `m_blob`: This is a model data in `BLOB` that holds the ONNX representation of the model.
- `"function" : "embedding"`: Indicates the function name for text embedding model.

- `"embeddingOutput" : "embedding"`: Specifies the output variable which contains the embedding results.
- `"input": {"input": ["DATA"]}`: Specifies a JSON object (`"input"`) that describes the input expected by the model. It specifies that there is an input named `"input"`, and its value should be an array with one element, `"DATA"`. This indicates that the model expects a single string input to generate embeddings.

Alternately, the `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` procedure can also accept a `BLOB` argument representing an ONNX file stored and loaded from OCI Object Storage. The following is an example to load an ONNX model stored in an OCI Object Storage.

```
DECLARE
  model_source BLOB := NULL;
BEGIN
  -- get BLOB holding onnx model
  model_source := DBMS_CLOUD.GET_OBJECT(
    credential_name => 'myCredential',
    object_uri => 'https://objectstorage.us-phoenix -1.oraclecloud.com/' ||
      'n/namespace -string/b/bucketname/o/myONNXmodel.onnx');

  DBMS_DATA_MINING.IMPORT_ONNX_MODEL(
    "myonnxmodel",
    model_source,
    JSON('{ function : "embedding" })
  );
END;
/
```

This PL/SQL block starts by initializing a `model_source` variable as a `BLOB` type, initially set to NULL. It then retrieves an ONNX model from Oracle Cloud Object Storage using the `DBMS_CLOUD.GET_OBJECT` procedure, specifying the credentials `(OBJ_STORE_CRED)` and the URI of the model. The ONNX model resides in a specific bucket named `bucketname` in this case, and is accessible through the provided URL. Then, the script loads the ONNX model into the `model_source` BLOB. The `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` procedure then imports this model into the Oracle Database as `myonnxmodel`. During the import, a JSON metadata specifies the model's function as `embedding`, for embedding operations.

See IMPORT_ONNX_MODEL Procedure and GET_OBJECT Procedure and Function to learn about the PL/SQL procedure.

Example: Importing a Pretrained ONNX Model to Oracle Database

The following presents a comprehensive step-by-step example of importing ONNX embedding and generating vector embeddings.

```
conn sys/<password>@pdb as sysdba
grant db_developer_role to dmuser identified by dmuser;
grant create mining model to dmuser;

create or replace directory DM_DUMP as '<work directory path>';
grant read on directory dm_dump to dmuser;
grant write on directory dm_dump to dmuser;
>conn dmuser/<password>@<pdbname>;
```

```
-- Drop the model if it exits
exec DBMS_VECTOR.DROP_ONNX_MODEL(model_name => 'doc_model', force =>
true);

-- Load Model
EXECUTE DBMS_VECTOR.LOAD_ONNX_MODEL(
    'DM_DUMP',
    'my_embedding_model.onnx',
    'doc_model',
    JSON('{"function" : "embedding", "embeddingOutput" :
"embedding"}'));
/
--Alternately, load the model
EXECUTE DBMS_DATA_MINING.IMPORT_ONNX_MODEL(
       'my_embedding_model.onnx',
    'doc_model',
    JSON('{"function" : "embedding",
    "embeddingOutput" : "embedding",
    "input": {"input": ["DATA"]}}')
    );

--check the attributes view
set linesize 120
col model_name format a20
col algorithm_name format a20
col algorithm format a20
col attribute_name format a20
col attribute_type format a20
col data_type format a20

SQL> SELECT model_name, attribute_name, attribute_type, data_type,
vector_info
FROM user_mining_model_attributes
WHERE model_name = 'DOC_MODEL'
ORDER BY ATTRIBUTE_NAME;


OUTPUT:

MODEL_NAME           ATTRIBUTE_NAME       ATTRIBUTE_TYPE
DATA_TYPE  VECTOR_INFO
-------------------- -------------------- --------------------
---------- ---------------
DOC_MODEL                INPUT_STRING         TEXT
VARCHAR2
DOC_MODEL                ORA$ONNXTARGET       VECTOR
VECTOR     VECTOR(128,FLOA

   T32)



SQL> SELECT MODEL_NAME, MINING_FUNCTION, ALGORITHM,
ALGORITHM_TYPE, MODEL_SIZE
```

```
FROM user_mining_models
WHERE model_name = 'DOC_MODEL'
ORDER BY MODEL_NAME;

OUTPUT:
MODEL_NAME           MINING_FUNCTION                ALGORITHM
ALGORITHM_ MODEL_SIZE
-------------------- ------------------------------ --------------------
---------- ----------
DOC_MODEL                EMBEDDING                      ONNX
NATIVE       17762137



SQL> select * from DM$VMDOC_MODEL ORDER BY NAME;

OUTPUT:
NAME                                     VALUE
----------------------------------------
----------------------------------------
Graph Description                        Graph combining g_8_torch_jit and
torch_
                                         jit
                                         g_8_torch_jit



                                         torch_jit



Graph Name                               g_8_torch_jit_torch_jit
Input[0]                                 input:string[1]
Output[0]                                embedding:float32[?,128]
Producer Name                            onnx.compose.merge_models
Version                                  1

6 rows selected.


SQL> select * from DM$VPDOC_MODEL ORDER BY NAME;

OUTPUT:
NAME                                     VALUE
----------------------------------------
----------------------------------------
batching                                 False
embeddingOutput                          embedding


SQL> select * from DM$VJDOC_MODEL;

OUTPUT:
METADATA
-----------------------------------------------------------------------------
---
```

```
{"function":"embedding","embeddingOutput":"embedding","input":{"input":
["DATA"]}}



--apply the model
SQL> SELECT TO_VECTOR(VECTOR_EMBEDDING(doc_model USING 'hello' as
data)) AS embedding;

-----------------------------------------------------------------------
---------
[-9.76553112E-002,-9.89954844E-002,7.69771636E-003,-4.16760892E-003,-9.
69305634E-002,
-3.01141385E-002,-2.63396613E-002,-2.98553891E-002,5.96499592E-002,4.13
885899E-002,
5.32859489E-002,6.57707453E-002,-1.47056757E-002,-4.18472625E-002,4.158
8001E-002,
-2.86354572E-002,-7.56499246E-002,-4.16395674E-003,-1.52879998E-001,6.6
0010576E-002,
-3.9013084E-002,3.15719917E-002,1.2428958E-002,-2.47651711E-002,-1.1685
1285E-001,
-7.82847106E-002,3.34323719E-002,8.03267583E-002,1.70483496E-002,-5.424
07483E-002,
6.54291287E-002,-4.81935125E-003,6.11041225E-002,6.64106477E-003,-5.47
```

Convert Pretrained Models to ONNX Format

OML4Py enables the use of text transformers from Hugging Face by converting them into ONNX format models. OML4Py also adds the necessary tokenization and post-processing. The resulting ONNX pipeline is then imported into the database and can be used to generate embeddings for AI Vector Search.

Note:

This feature will **only** work on OML4Py client. It is not supported on the OML4Py server.

If you do not have a pretrained embedding model in ONNX-format to generate embeddings for your data, Oracle offers a Python utility package that downloads pretrained models from an external source, converts the model to ONNX format augmented with pre-processing and post-processing steps, and imports the resulting ONNX-format model into Oracle Database. Use the `DBMS_VECTOR.LOAD_ONNX_MODEL` procedure to import the file as a mining model. Then leverage the in-database ONNX Runtime with the ONNX model to produce vector embeddings.

At a high level, the Python utility package performs the following tasks:

- Downloads the pretrained model from external source to your system
- Augments the model with pre-processing and post-processing steps and creates a new ONNX model
- Validates the augmented ONNX model

- Loads into the database as a mining model or optionally exports to a file

The Python utility can take any of the models in the preconfigured list as input. Alternatively, you can use the built-in template that contains common configurations for certain groups of models such as text-based models. To understand what a preconfigured list, what is a built-in template is, and how to use them, read further.

Limitations

This table describes the limitations of the Python utility package.

Note:

This feature is available with the OML4Py client only.

Parameter	Description
`Transformer Model Type`	Currently supported only for text transformers.
`Model Size`	Model size should be less than 1GB. Quantization can help reduce the size.
`Tokenizers`	Must be either `BERT`, `GPT2`, `SENTENCEPIECE`, or `ROBERTA`.

Preconfigured List of Models

Preconfigured list of models are common models from external resource repositories that are provided with the Python utility. The preconfigured models have an existing specification. Users can create their own specification using the text template as a starting point. To get a list of all model names in the preconfigured list, you can use the `show_preconfigured` function.

Templates

The Python utility package provides built-in text template for you to configure the pretrained models with pre-processing and post-processing operations. The template has a default specification for the pretrained models. This specification can be changed or augmented to create custom configurations. The text template uses Mean Pooling and Normalization as post-processing operations by default.

The Python utility package provides the following classes:

- `EmbeddingModelConfig`
- `EmbeddingModel`

To learn more about the Python classes, their properties, and to configure the properties, see Python Classes to Convert Pretrained Models to ONNX Models.

To use the Python utility, ensure that you have the following:

- OML4Py Client running on Linux X64 for On-Premises Databases
- Python 3.12 (the earlier versions are not compatible)

.

1. Start Python in your work directory.

   ```
   $python3


   Python 3.12.2 | (main, Feb 27 2024, 17:35:02) [GCC 11.2.0] on linux
   Type "help", "copyright", "credits" or "license" for more
   information.
   ```

2. On the OML4Py client, load the Python classes:

   ```
   from oml.utils import EmbeddingModel, EmbeddingModelConfig
   ```

3. You can get a list of all preconfigured models by running the following:

   ```
   EmbeddingModelConfig.show_preconfigured()
   ```

4. To get a list of available templates:

   ```
   EmbeddingModelConfig.show_templates()
   ```

5. Choose from:
   - Generate an ONNX file from the preconfigureded model "sentence-transformers/all-MiniLM-L6-v2":

     ```
     #generate from preconfigureded model "sentence-transformers/all-
     MiniLM-L6-v2"
     em = EmbeddingModel(model_name="sentence-transformers/all-MiniLM-
     L6-v2")
     em.export2file("your_preconfig_file_name",output_dir=".")
     ```

   - Generate an ONNX model from the preconfigured model "sentence-transformers/all-MiniLM-L6-v2" in the database:

     ```
     #generate from preconfigureded model "sentence-transformers/all-
     MiniLM-L6-v2"
     em = EmbeddingModel(model_name="sentence-transformers/all-MiniLM-
     L6-v2")
     em.export2db("your_preconfig_model_name")
     ```

   - Generate an ONNX file using the provided text template:

     ```
     #generate using the "text" template
     config =
     EmbeddingModelConfig.from_template("text",max_seq_length=512)
     em = EmbeddingModel(model_name="intfloat/e5-small-
     v2",config=config)
     em.export2file("your_template_file_name",output_dir=".")
     ```

   Let's understand the code:

`from oml.utils import EmbeddingModel, EmbeddingModelConfig`: This line imports two classes, `EmbeddingModel` and `EmbeddingModelConfig`.

In the preconfigured models first example:

- `em = EmbeddingModel(model_name="sentence-transformers/all-MiniLM-L6-v2")` creates an instance of the `EmbeddingModel` class, loading a pretrained model specified by the `model_name` parameter. `em` is the embedding model object. `sentence-transformers/all-MiniLM-L6-v2` is the model name for computing sentence embeddings. This is the model name under Hugging Face. Oracle supports models from Hugging Face.
- The `export2file` command creates an ONNX format model with a user-specified model name in the database. `your_preconfig_file_name` is a user defined ONNX model file name.
- `output_dir="."` specifies the output directory where the file will be saved. The `"."` denotes the current directory (that is, the directory from which the script is running).

In the preconfigured models second example:

- `em = EmbeddingModel(model_name="sentence-transformers/all-MiniLM-L6-v2")` creates an instance of the `EmbeddingModel` class, loading a pretrained model specified by the `model_name` parameter. `em` is the embedding model object. `sentence-transformers/all-MiniLM-L6-v2` is the model name for computing sentence embeddings. This is the model name under Hugging Face. Oracle supports models from Hugging Face.
- The `export2db` command creates an ONNX format model with a user defined model name in the database. `your_preconfig_model_name` is a user defined ONNX model name.

In the template example:

- `config = EmbeddingModelConfig.from_template("text", max_seq_length=512)`: This line creates a configuration object for an embedding model using a method called `from_template`. The `"text"` argument indicates the name of the template. The `max_seq_length=512` parameter specifies the maximum length of input to the model as number of tokens. There is no default value. Specify this value for models that are not preconfigured.
- `em = EmbeddingModel(model_name="intfloat/e5-small-v2", config=config)` initializes an `EmbeddingModel` instance with a specific model and the previously defined configuration. The `model_name="intfloat/e5-small-v2"` argument specifies the name or identifier of the pretrained model to be loaded.
- The `export2file` command creates an ONNX format model with a user defined model name in the database. `your_template_file_name` is a user defined ONNX model name.
- `output_dir="."` specifies the output directory where the file will be saved. The `"."` denotes the current directory (that is, the directory from which the script is running).

> **Note:**
>
> - The model size is limited to 1 gigabyte. For models larger than 400MB, Oracle recommends quantization.
>
>   **Quantization** reduces the model size by converting model weights from high-precision representation to low-precision format. The quantization option converts the weights to INT8. The smaller model size enables you to cache the model in shared memory further improving the performance.
> - The `.onnx` file is created with opset version 17 and ir version 8. For more information about these version numbers, see https://onnxruntime.ai/docs/reference/compatibility.html#onnx-opset-support.

6. Exit Python.

   ```
   exit()
   ```

7. Inspect if the converted models are present in your directory.

   > **Note:**
   >
   > ONNX files are only created when `export2file` is used. If `export2db` is used, no ONNX files will be generated.

   ```
   ls-ltr *.onnx
   ```

   ```
   your_preconfig_file_name.onnx
   your_template_file_name.onnx
   ```

   The Python utility package validates the embedding text model before you can run them using ONNX Runtime. Oracle supports ONNX embedding models that conform to `string` as input and `float32 [<vector dimension>]` as output.

   If the input or output of the model doesn't conform to the description, you receive an error during the import.

`DBMS_VECTOR.LOAD_ONNX_MODEL` or `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` are only needed if `export2file` was used instead of `export2db`. Use the resulting ONNX format model in the `DBMS_VECTOR.LOAD_ONNX_MODEL` procedure or in the `DBMS_DATA_MINING.IMPORT_ONNX_MODEL` procedure and generate vector embeddings using the `VECTOR_EMBEDDING` SQL operator.

- Python Classes to Convert Pretrained Models to ONNX Models
  Explore the functions and attributes of the `EmbeddingModelConfig` class and `EmbeddingModel` class within Python. These classes are designed to configure pretrained embedding models.

See Also:

- *Oracle Database SQL Language Reference* for information about the `VECTOR_EMBEDDING` SQL function
- *Oracle Database PL/SQL Packages and Types Reference* for information about the `IMPORT_ONNX_MODEL` procedure
- *Oracle Database PL/SQL Packages and Types Reference* for information about the `LOAD_ONNX_MODEL` procedure
- *Oracle Machine Learning for SQL Concepts* for more information about importing pretrained embedding models in ONNX format and generating vector embeddings
- https://onnx.ai/onnx/intro/ for ONNX documentation

Python Classes to Convert Pretrained Models to ONNX Models

Explore the functions and attributes of the `EmbeddingModelConfig` class and `EmbeddingModel` class within Python. These classes are designed to configure pretrained embedding models.

EmbeddingModelConfig

The `EmbeddingModelConfig` class contains the properties required for the package to perform downloading, exporting, augmenting, validation, and storing of an ONNX model. The class provides access to configuration properties using the dot operator. As a convenience, well-known configurations are provided as templates.

Parameters

This table describes the functions and properties of the `EmbeddingModelConfig` class.

Functions	Parameter Type	Returns	Description
`from_template(name, **kwargs)`	• `name` (`String`): The name of the template • `**kwargs`: template properties to override or add	Instance of `EmbeddingModelConfig`	A static function that creates an `EmbeddingModelConfig` object based on a predefined template given by the name parameter. You can use named arguments to override the template properties.
`show_templates()`	NA	List of existing templates	A static function that returns a list of existing templates by name.

Functions	Parameter Type	Returns	Description
`show_preconfigured()`	• `include_properties` (`bool,optional`): A flag indicating whether properties should be included in the results. Defaults to `False` so only names will be included by default. • `model_name` (`str,optional`): A model name to filter by when including properties. This argument will be ignored if `include_properties` is `False`. Otherwise only the properties of this model will be included in the results.	A list of preconfigured model names or properties.	Shows a list of preconfigured model names, or properties. By default, this function returns a list of names only. If the properties are required, pass the `include_properties` parameter as `True`. The returned list will contain a single dict where each key of the dict is the name of a preconfigured model and the value is the property set for that model. Finally, if only a single set of properties for a specific model is required, pass the name of the model in the `model_name` parameter (the `include_properties` parameter should also be `True`). This will return a list of a single dict with the properties for the specified model.

Template Properties

The text template has configuration properties shown below:

```
"do_lower_case": true,
"post_processors":[{"name":"Pooling","type":"mean"},
{"name":"Normalize"}]
```

Note:

All other properties in the Properties table will take the default values. Any property without a default value must be provided when creating the `EmbeddingModelConfig` instance.

Properties

This table shows all properties that can be configured. preconfigured models already have these properties set to specific values. Templates will use the default values unless a user overrides it when using the `from_template` function on `EmbeddingModelConfig`.

Property	Description
`post_processors`	An array of post_processors that will be loaded after the model is loaded or initialized. The list of known and supported post_processors is provided later in this section. Templates may define a list of post_processors for the types of models they support. Otherwise, an empty array is the default.
`max_seq_length`	This property is applicable for text-based models only. The maximum length of input to the model as number of tokens. There is no default value. Specify this value for models that are not preconfigured.
`do_lower_case`	Specifies whether or not to lowercase the input when tokenizing. The default value is `True`.
`quantize_model`	Perform quantization on the model. This could greatly reduce the size of the model as well as speed up the process. It may however result in different results for the embedding vector (against the original model) and possibly small reduction in accuracy. The default value is `False`.
`distance_metrics`	An array of names of suitable distance metrics for the model. The names must be name of distance metrics used for Oracle vector distance operator. Only used when exporting the model to the database. Supported list is ["`EUCLIDEAN`","`COSINE`","`MANHATTAN`","`HAMMING`","`DOT`","`EUCLIDEAN_SQUARED`"]. The default value is an empty array.
`languages`	A array of language (Abbreviation) supported in the Database. Only used when exporting the model to the database. For a supported list of languages, see Languages. The default value is an empty array.
`use_float16`	Specifies whether or not to convert the exported onnx model to float16. The default value is `False`.

Properties of post_processors

This table describes the built-in post_processors and their configuration parameters.

post_processor	Parameters	Description
`Pooling`	• `name`: `Pooling`. • `type`: Valid values should be `mean`(Default), `max`, `cls`	The Pooling post_processor summarizes the output of the transformer model into a fixed-length vector.
`Normalize`	• `name`: Specify `Normalize`	The Normalize post_processor bounds the vector values to a range using L2 normalization.

post_processor	Parameters	Description
`Dense`	• `name`: Dense • `in_features`: Input feature size • `out_features`: Output feature size • `bias`: Whether to learn an additive bias. The default value is `True`. • `activation_function`: Activation function of the dense layer. Currently only supports `Tanh` as the activation function.	Applies transformation to the incoming data.

Example: Configure post_processors

In this example, you override the post_processors in the sentence-transformers template with a `Max` Pooling post_processor followed by Normalization.

```
config = EmbeddingModelConfig.from_template("text")
config.post_processors = [{"name":"Pooling","type":"max"},
{"name":"Normalize"}]
```

EmbeddingModel

Use the `EmbeddingModel` class to convert transformer models to the ONNX format with post_processing steps embedded into the final model.

Parameters

This table describes the signature and properties of the `EmbeddingModel` class.

Functions	Parameters	Description
`EmbeddingModel(model_name,configuration=None,settings={})`	• `model_name`: The name of the model to be used. For example, `medicalai/ClinicalBERT` • `configuration`: An initialized `EmbeddingModelConfig` object. This parameter must be specified when using a template. If not specified, the model will be assumed to be a preconfigured model. • `settings`: A dictionary of various settings that are global and control various operations such as logging levels and locations for files.	Creates a new instance of the `EmbeddingModel` class.

Settings

The settings object is a dictionary passed to the `EmbeddingModel` class. It provides global properties for the `EmbeddingModel` class that are used for non-model-specific operations, such as logging.

Property	Default Value	Description
`cache_dir`	`$HOME/.cache/OML`	The base directory used for downloads. Model files will be downloaded from the repository to directories relative to the `cache_dir`. If the `cache_dir` does not exist at time of execution, it will be created.

Property	Default Value	Description
`logging_level`	`ERROR`	The level for logging. Valid values are ['DEBUG', 'INFO', 'WARNING', 'ERROR', 'CRITICAL']. **Note:** This log level is also applied globally to all python packages and is also mapped to the ONNX Runtime libraries.
`force_download`	`False`	Forces download of model files instead of reloading from cache.
`ignore_checksum_error`	`False`	Ignores any errors caused by mismatch in checksums when using preconfigured models.

Functions

This table describes the function and properties of the `EmbeddingModel` class.

Function	Parameters	Description
`export2file(export_name,output_dir=None)`	• `export_name(string)`: The name of the file. The file will be saved with the file extension `.onnx` • `output_dir(string)`: An optional output directory. If not specified the file will be saved to the current directory	Exports the model to a file.
`export2db(export_name)`	• `export_name(string)`: The name that will be used for the mining model object. This name must be compliant with existing rules for object names in the database.	Exports the model to the database.

Example: Preconfigured Model

This example illustrates the preconfigured embedding model that comes with the Python package. You can use this model without any additional configurations.

```
"sentence-transformers/distiluse-base-multilingual-cased-v2": {
        "max_seq_length": 128,
        "do_lower_case": false,
        "post_processors":[{"name":"Pooling","type":"mean"},
{"name":"Dense","in_features":768, "out_features":512, "bias":true,
"activation_function":"Tanh"}],
        "quantize_model":true,
        "distance_metrics": ["COSINE"],
        "languages": ["ar", "bg", "ca", "cs", "dk", "d", "us", "el", "et",
"fa", "sf", "f", "frc", "gu", "iw", "hi", "hr", "hu", "hy", "in", "i", "ja",
"ko", "lt", "lv", "mk", "mr", "ms", "n", "nl", "pl", "pt", "ptb", "ro",
"ru", "sk", "sl", "sq", "lsr", "s", "th", "tr", "uk", "ur", "vn", "zhs",
"zht"]
    }
```

Generate Vector Embeddings Using Vector Utilities Leveraging Third-Party REST APIs

Oracle AI Vector Search offers vector utilities (SQL and PL/SQL tools) to automatically generate vector embeddings from your unstructured data.

You can call either *Vector Utility SQL functions* or *Vector Utility PL/SQL packages* to transform unstructured data into vector embeddings.

- Understand the Stages of Data Transformations
  Your input data may travel through different stages before turning into a vector.
- Use SQL Functions to Generate Embeddings
  Choose to implement Vector Utility SQL functions to perform parallel or on-the-fly chunking and embedding operations, within Oracle Database.

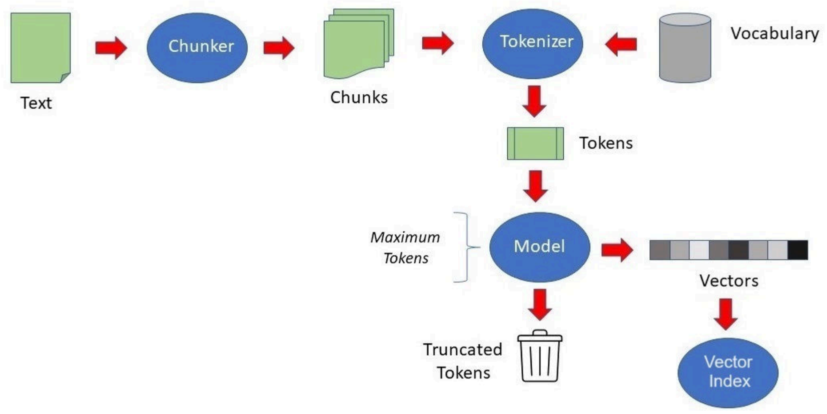
- Use PL/SQL Packages to Generate Embeddings
  Choose to implement Vector Utility PL/SQL packages to perform chunking, embedding, and text generation operations along with text processing and similarity search, within and outside Oracle Database.

Understand the Stages of Data Transformations

Your input data may travel through different stages before turning into a vector.

For example, you may first transform textual data (such as a PDF document) into plain text, then break the resulting text into smaller pieces of text (chunks) to finally create vector embeddings on each chunk.

As shown in the following image, input data passes through a pipeline of optional stages from *Text* to *Chunks* to *Tokens* to *Vectors*, with *Vector Index* as the endpoint:



Prepare: Text and Chunks

This stage prepares your unstructured data to ensure that it is in a format that can be processed by vector embedding models.

To prepare large unstructured textual data (for example, a PDF or Word document), you first transform the data into plain text and then pass the resulting text through *Chunker*. The chunker then splits the text into smaller chunks using a process known as **chunking**. A single document may be split into many chunks, each transformed into a vector.

Chunks are pieces of words (to capture specific words or word pieces), sentences (to capture a specific meaning), or paragraphs (to capture broader themes). Later, you will learn about several chunking parameters and techniques to define so that each chunk contains relevant and meaningful context.

Embed: Tokens and Vectors

You now pass the extracted chunks as input to *Model* (a declared vector embedding model) for generating vector embeddings on each chunk. This stage makes these chunks searchable.

The chunks are first passed through *Tokenizer* of the model to split into words or word pieces, known as **tokens**. The model then embeds each token into a vector representation.

Tokenizers used by embedding models frequently have limits on the size of the input text they can deal with, so chunking is needed to avoid loss of text when generating embeddings. If input text is larger than the maximum input limit imposed by the model, then the text gets truncated unless it is split up into appropriate-sized segments or chunks. Chunking is not needed for smaller documents, text strings, or summarized texts that meet this maximum input limit.

The chunker must select a text size that approximates the maximum input limit of your model. The actual number of tokens depends on the specified tokenizer for the model, which typically uses a **vocabulary** list of words, numbers, punctuations, and pieces of tokens.

A vocabulary contains a set of tokens that are collected during a statistical training process. Each tokenizer uses a different vocabulary format to process text into tokens, that is, the BERT multilingual model uses Word-Piece encoding and the GPT model uses Byte-Pair encoding.

For example, the BERT model tokenizes the following four words:

```
Embedding usecase for chunking
```

as the following eight tokens and also includes `##` (number signs) to indicate non-initial pieces of words:

```
Em ##bedd ##ing use ##case for chunk ##ing
```

Vocabulary files are included as part of a model's distribution. You can supply a vocabulary file (recognized by your model's tokenizer) to the chunker beforehand, so that it can correctly estimate the token count of your input data when chunking.

Populate and Query: Vector Indexes

Finally, you store the semantic content of your input data as vectors in *Vector Index*. You can now implement combined similarity and relational queries to retrieve relevant results using the extracted vectors.

Use SQL Functions to Generate Embeddings

Choose to implement Vector Utility SQL functions to perform parallel or on-the-fly chunking and embedding operations, within Oracle Database.

Vector Utility SQL functions are intended for a direct and quick interaction with data, within pure SQL.

To get chunks, this function uses the in-house implementation with Oracle Database. To get an embedding, this function uses ONNX embedding models that you load into the database (and not third-party REST providers).

VECTOR_CHUNKS

Use the `VECTOR_CHUNKS` SQL function if you want to split plain text into chunks (pieces of words, sentences, or paragraphs) in preparation for the generation of embeddings, to be used with a vector index.

For example, you can use this function to build a standalone Text Chunking system that lets you break down a large amount of text into smaller yet semantically meaningful chunks. You can experiment with your chunks by inspecting and accordingly amending the chunking results and then proceed further.

For detailed information, see VECTOR_CHUNKS in *Oracle Database SQL Language Reference*.

VECTOR_EMBEDDING

Use the `VECTOR_EMBEDDING` function if you want to generate a single vector embedding for different data types.

For example, you can use this function in information-retrieval applications or chatbots, where you can generate a query vector on the fly from a user's natural language text input.

For detailed information, see VECTOR_EMBEDDING in *Oracle Database SQL Language Reference*.

Use PL/SQL Packages to Generate Embeddings

Choose to implement Vector Utility PL/SQL packages to perform chunking, embedding, and text generation operations along with text processing and similarity search, within and outside Oracle Database.

Vector Utility PL/SQL APIs work with both the ONNX embedding models (loaded into the database) and third-party REST providers, such as Cohere, Google AI, Hugging Face, Oracle Cloud Infrastructure (OCI) Generative AI, OpenAI, or Vertex AI.

These packages are made up of subprograms, such as *chainable utility functions* and *vector helper procedures*.

- Terms of Using Vector Utility PL/SQL Packages
  You must understand the terms of using REST APIs that are part of Vector Utility PL/SQL packages.
- About Chainable Utility Functions and Common Use Cases
  These are intended to be a set of chainable and flexible "stages" through which you pass your input data to transform into a different representation, including vectors.
- About Vector Helper Procedures
  Vector helper procedures let you configure authentication credentials and language-specific data, for use in chainable utility functions.
- Supplied Vector Utility PL/SQL Packages
  Use either a lightweight `DBMS_VECTOR` package or a more advanced `DBMS_VECTOR_CHAIN` package with full capabilities.
- Supported Third-Party Provider Operations
  Review the list of third-party REST providers that are supported with Vector Utility PL/SQL packages and the corresponding API calls allowed for each of those.
- Validate JSON Input Parameters
  You can optionally validate the structure of your JSON input to the `DBMS_VECTOR.UTL` and `DBMS_VECTOR_CHAIN.UTL` functions, which use JSON to define their input parameters.

Terms of Using Vector Utility PL/SQL Packages

You must understand the terms of using REST APIs that are part of Vector Utility PL/SQL packages.

Some of the Vector Utility PL/SQL APIs enable you to perform embedding, summarization, and text generation operations outside Oracle Database, by using third-party REST providers (such as Cohere, Google AI, Hugging Face, Generative AI, OpenAI, or Vertex AI).

WARNING:

Certain features of the database may allow you to access services offered separately by third-parties, for example, through the use of JSON specifications that facilitate your access to REST APIs.

Your use of these features is solely at your own risk, and you are solely responsible for complying with any terms and conditions related to use of any such third-party services. Notwithstanding any other terms and conditions related to the third-party services, your use of such database features constitutes your acceptance of that risk and express exclusion of Oracle's responsibility or liability for any damages resulting from such access.

About Chainable Utility Functions and Common Use Cases

These are intended to be a set of chainable and flexible "stages" through which you pass your input data to transform into a different representation, including vectors.

Supplied Chainable Utility Functions

You can combine a set of chainable utility (`UTL`) functions together in an end-to-end pipeline.

Each pipeline or **transformation chain** can include a single function or a combination of functions, which are applied to source documents as they are transformed into other representations (text, chunks, summary, or vector). These functions are chained together, such that the output from one function is used as an input for the next.

Each chainable utility function performs a specific task of transforming data into other representations, such as converting data to text, converting text to chunks, or converting the extracted chunks to embeddings.

At a high level, the supplied chainable utility functions include:

Function	Description
`UTL_TO_TEXT()`	Converts a document (for example, MS Word, HTML, or PDF) to plain text
`UTL_TO_CHUNKS()`	Converts plain text to chunks
`UTL_TO_EMBEDDING()`	Converts plain text to a single embedding (`VECTOR`)
`UTL_TO_EMBEDDINGS()`	Converts an array of chunks (`VECTOR_ARRAY_T`) to an array of embeddings (`VECTOR_ARRAY_T`)
`UTL_TO_SUMMARY()`	Converts plain text to a summary
`UTL_TO_GENERATE_TEXT()`	Generates text for a prompt or input string

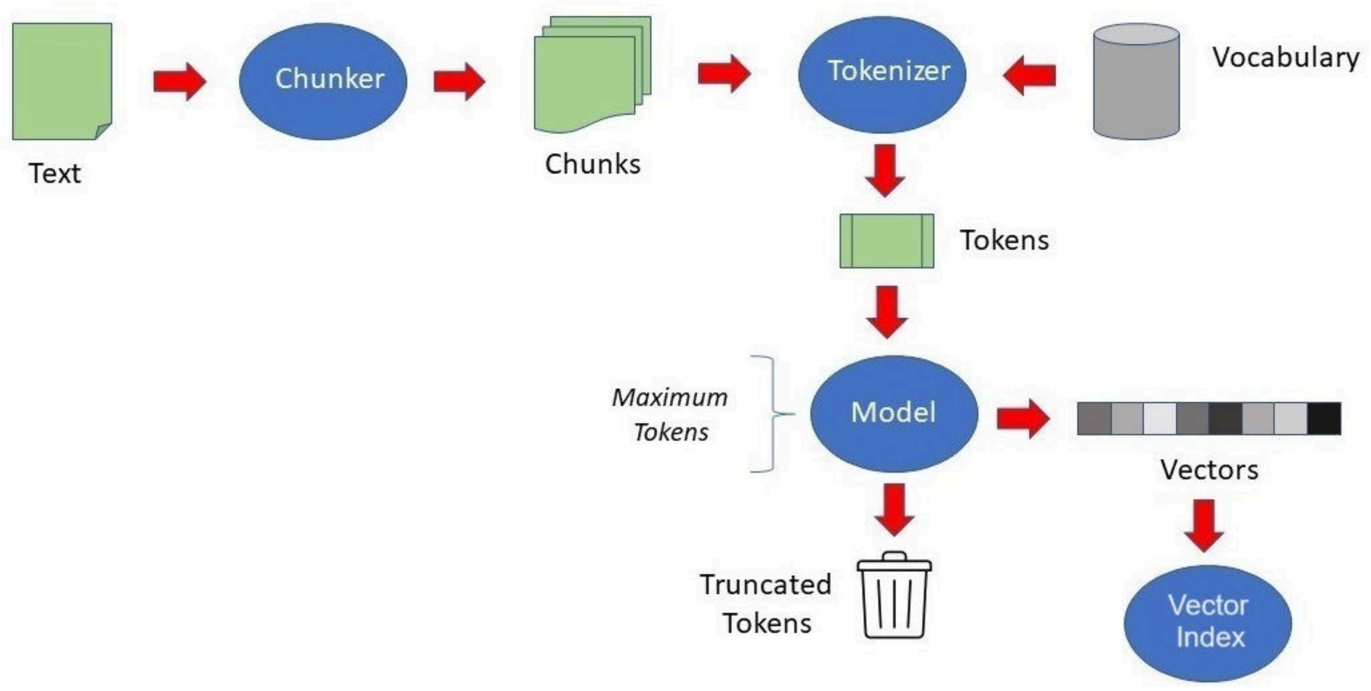
Sequence of Chains

Chainable utility functions are designed to be flexible and modular. You can create transformation chains in various sequences, depending on your use case.

For example, you can directly extract vectors from a PDF file by creating a chain of the `UTL_TO_TEXT`, `UTL_TO_CHUNKS`, and `UTL_TO_EMBEDDINGS` chainable utility functions.

As shown in the following diagram, a *file-to-text-to-chunks-to-embeddings* chain performs a set of operations in this order:

1. Converts a PDF file to plain text (using `UTL_TO_TEXT`)
2. Splits the resulting text into appropriate-sized chunks (using `UTL_TO_CHUNKS`)
3. Generates vector embeddings on each chunk (using `UTL_TO_EMBEDDINGS`)



Common Use Cases

Let us look at some common use cases to understand how you can customize and apply these chains:

Single-Step or Direct Transformation

- **Document to vectors**:

  As discussed earlier, a common use case might be to automatically generate vectors from documents.

  You can convert a set of documents to plain text, split the resulting text into smaller chunks to finally generate embeddings on each chunk, in a single *file-to-text-to-chunks-to-embeddings* chain.

  See Convert File to Embeddings.

- **Document to vectors, with chunking and summarization**:

  Another use case might be to generate a short summary of documents and then automatically extract vectors from that summary.

After generating the summary, you can either generate a single vector (using `UTL_TO_EMBEDDING`) or chunk it and then generate multiple vectors (using `UTL_TO_EMBEDDINGS`).

  – You can convert the document to plain text, summarize the text into a concise gist to finally create a single embedding on the summarized text, in a *file-to-text-to-summary-to-embedding* chain.
  – You can convert the document to plain text, summarize the text into a gist, split the gist into chunks to finally create multiple embeddings on each summarized chunk, in a *file-to-text-to-summary-to-chunks-to-embeddings* chain.

While both the chunking and summarization techniques make text smaller, they do so in different ways. Chunking just breaks the text into smaller pieces, whereas summarization extracts a salient meaning and context of that text into free-form paragraphs or bullet points.

By summarizing the entire document and appending the summary to each chunk, you get the best of both worlds, that is, an individual piece that also has a high-level understanding of the overall document.

- **Prompt to text**:

  You can generate a response directly based on a prompt.

  A prompt can be an input string, such as a question that you ask a Large Language Model (LLM). For example, "`What is Oracle Text?`". A prompt can also be a command, such as "`Summarize the following ...`", "`Draft an email asking for ...`", or "`Rewrite the following ...`", and can include results from a search.

  See Generate Text for a Prompt: PL/SQL Example.

Step-by-Step or Parallel Transformation

- **Text to vector**:

  A common use case might be information retrieval applications or chatbots, where you can on the fly generate an embedding from a user's natural language text query.

  You can convert the input text to a query vector (and then run it against the vector index for a fast similarity search), in a *text-to-embedding* chain.

  See Convert Text String to Embedding.

- **Text to chunks**:

  Another use case might be to build a standalone Text Chunking system to break down a large amount of text into smaller yet semantically meaningful pieces, in a *text-to-chunks* chain.

  This method also gives you more flexibility to experiment with your chunks, where you can create, inspect, and accordingly amend the chunking results and then proceed further.

  See Convert Text to Chunks With Custom Chunking Specifications and Convert File to Text to Chunks to Embeddings.

- **Text to summary**:

  You can build a standalone Text Summarization system to convert a large amount of text into a summary, in a *text-to-summary* chain.

  This method also gives you more flexibility to experiment with your summaries, where you can create, inspect, and accordingly amend the summarization results and then proceed further.

See Convert Text String to Summary.

Schedule Vector Utility Packages

Some of the transformation chains may take a long time depending on your workload and implementation, thus you can schedule to run Vector Utility PL/SQL packages in the background.

The `DBMS_SCHEDULER` PL/SQL package helps you effectively schedule these packages, without manual intervention.

For information on how to create, run, and manage jobs with Oracle Scheduler, see *Oracle Database Administrator’s Guide*.

About Vector Helper Procedures

Vector helper procedures let you configure authentication credentials and language-specific data, for use in chainable utility functions.

At a high level, the supplied vector helper procedures include:

- **Credential helper procedures** to securely manage authentication credentials, which are used to access third-party providers when making REST API calls.

Function	Description
`CREATE_CREDENTIAL`	Creates a credential name for securely storing user authentication credentials in the database.
`DROP_CREDENTIAL`	Drops an existing credential name.

- **Chunker helper procedures** to manage custom vocabulary and language data, which are used when chunking user data.

Function	Description
`CREATE_VOCABULARY`	Loads your own vocabulary file into the database.
`DROP_VOCABULARY`	Removes the specified vocabulary data from the database.
`CREATE_LANG_DATA`	Loads your own language data file (abbreviation tokens) into the database.
`DROP_LANG_DATA`	Removes abbreviation data for a given language from the database.

Related Topics

- Vector Utilities-Related Views
  These views display language-specific data (abbreviation token details) and vocabulary data related to the Oracle AI Vector Search SQL and PL/SQL utilities.

Supplied Vector Utility PL/SQL Packages

Use either a lightweight `DBMS_VECTOR` package or a more advanced `DBMS_VECTOR_CHAIN` package with full capabilities.

- `DBMS_VECTOR`:

  This package simplifies common operations with Oracle AI Vector Search, such as chunking text into smaller segments, extracting vector embeddings from user data, or generating text for a given prompt.

Subprogram	Operation	Provider	Implementation
Chainable Utility Functions	`UTL_TO_CHUNKS` to perform chunking	Oracle Database	Calls the `VECTOR_CHUNKS` SQL function under the hood
	`UTL_TO_EMBEDDING` and `UTL_TO_EMBEDDINGS` to generate one or more embeddings	Oracle Database	Calls the ONNX embedding model that you load into the database
		Third-party REST providers	Calls the specified third-party embedding model
	`UTL_TO_GENERATE_TEXT` to generate text for prompts	Third-party REST providers	Calls the specified third-party text generation model
Credential Helper Procedures	`CREATE_CREDENTIAL` and `DROP_CREDENTIAL` to manage credentials for third-party service providers	Oracle Database	Stores credentials securely for use in Chainable Utility Functions

For detailed information on this package, see DBMS_VECTOR in *Oracle Database PL/SQL Packages and Types Reference*.

- `DBMS_VECTOR_CHAIN`:

  This package provides chunking and embedding functions along with some text generation and summarization capabilities. It is more suitable for text processing with similarity search, using functionality that can be pipelined together for an end-to-end search.

  This package requires you to install the `CONTEXT` component of Oracle Text, an Oracle Database technology that provides indexing, term extraction, text analysis, text summarization, word and theme searching, and other utilities.

Subprogram	Operation	Provider	Implementation
Chainable Utility Functions	`UTL_TO_TEXT` to extract plain text data from documents	Oracle Database	Uses the Oracle Text component (`CONTEXT`) of Oracle Database
	`UTL_TO_CHUNKS` to perform chunking	Oracle Database	Calls the `VECTOR_CHUNKS` SQL function under the hood
	`UTL_TO_EMBEDDING` and `UTL_TO_EMBEDDINGS` to generate one or more embeddings	Oracle Database	Calls the ONNX embedding model that you load into the database
		Third-party REST providers	Calls the specified third-party embedding model
	`UTL_TO_SUMMARY` to generate summaries	Oracle Database	Uses Oracle Text
		Third-party REST providers	Calls the specified third-party text summarization model
	`UTL_TO_GENERATE_TEXT` to generate text for prompts	Third-party REST providers	Calls the specified third-party text generation model
Credential Helper Procedures	`CREATE_CREDENTIAL` and `DROP_CREDENTIAL` to manage credentials for third-party service providers	Oracle Database	Stores credentials securely for use in Chainable Utility Functions

Subprogram	Operation	Provider	Implementation
Chunker Helper Procedures	`CREATE_VOCABULARY` and `DROP_VOCABULARY` to manage custom token vocabularies	Oracle Database	Uses Oracle Text
	`CREATE_LANG_DATA` and `DROP_LANG_DATA` to manage language-specific data (abbreviation tokens)	Oracle Database	Uses Oracle Text

Due to underlying dependance on the text processing capabilities of Oracle Text, note that both the `UTL_TO_TEXT` and `UTL_TO_SUMMARY` chainable utility functions and all the chunker helper procedures are available only in this package through Oracle Text.

For detailed information on this package, see DBMS_VECTOR_CHAIN in *Oracle Database PL/SQL Packages and Types Reference*.

Related Topics

- Supported Third-Party Provider Operations
  Review the list of third-party REST providers that are supported with Vector Utility PL/SQL packages and the corresponding API calls allowed for each of those.

Supported Third-Party Provider Operations

Review the list of third-party REST providers that are supported with Vector Utility PL/SQL packages and the corresponding API calls allowed for each of those.

The supported third-party REST providers are:

- Cohere
- Generative AI
- Google AI
- Hugging Face
- OpenAI
- Vertex AI

The corresponding REST calls allowed for each operation are:

- DBMS_VECTOR.UTL_TO_EMBEDDING and DBMS_VECTOR.UTL_TO_EMBEDDINGS
- DBMS_VECTOR_CHAIN.UTL_TO_EMBEDDING and DBMS_VECTOR_CHAIN.UTL_TO_EMBEDDINGS
- DBMS_VECTOR_CHAIN.UTL_TO_SUMMARY
- DBMS_VECTOR.UTL_TO_GENERATE_TEXT
- DBMS_VECTOR_CHAIN.UTL_TO_GENERATE_TEXT

Validate JSON Input Parameters

You can optionally validate the structure of your JSON input to the `DBMS_VECTOR.UTL` and `DBMS_VECTOR_CHAIN.UTL` functions, which use JSON to define their input parameters.

The JSON data is schemaless, so the amount of validation that Vector Utility package APIs do at runtime is minimal for better performance. The APIs validate only the mandatory JSON parameters, that is, the parameters that you supply for the APIs to run (not optional JSON parameters and attributes).

Before calling an API, you can use subprograms in the `DBMS_JSON_SCHEMA` package to test whether the input data to be specified in the `PARAMS` clause is valid with respect to a given JSON schema. This offers more flexibility and also ensures that only schema-valid data is inserted in a JSON column.

Validate JSON input parameters for the `DBMS_VECTOR.UTL` and `DBMS_VECTOR_CHAIN.UTL` functions against the following schema:

- **For the Database Provider**:
  - `SCHEMA_CHUNK`

```
{ "title" : "utl_to_chunks",
  "description" : "Chunk parameters",
  "type" : "object",
  "properties" : {
    "by"           : {"type" : "string", "enum" : [ "chars",
"characters", "words", "vocabulary" ]   },
    "max"          : {"type" : "string", "pattern" : "^[1-9]
[0-9]*$" },
    "overlap"      : {"type" : "string", "pattern" : "^[0-9]+$" },
    "split"        : {"type" : "string", "enum" : [ "none",
"newline", "blankline", "space", "recursively", "custom" ]  },
    "vocabulary"   : {"type" : "string"  },
    "language"     : {"type" : "string"  },
    "normalize"    : {"type" : "string", "enum" : [ "all", "none",
"options" ]  },
      "norm_options" : {"type" : "array",  "items": {  { "type":
"string", "enum": ["widechar", "whitespace", "punctuation"] }  },
    "custom_list"  : {"type" : "array",  "items": { "type":
"string" }  },
    "extended"     : {"type" : "boolean" } },
  "additionalProperties" : false
}
```

  - `SCHEMA_VOCAB`

```
{ "title" : "create_vocabulary",
  "description" : "Create vocabulary parameters",
  "type" : "object",
  "properties" : {
    "table_name"      : {"type" : "string" },
    "column_name"     : {"type" : "string" },
    "vocabulary_name" : {"type" : "string" },
    "format"          : {"type" : "string", "enum" : [ "BERT",
"GPT2", "XLM" ]  },
    "cased"           : {"type" : "boolean" } },
  "additionalProperties" : false,
  "required" : [ "table_name", "column_name", "vocabulary_name" ]
}
```

– SCHEMA_LANG

```
{ "title" : "create_lang_data",
  "description" : "Create language data parameters",
  "type" : "object",
  "properties" : {
    "table_name"      : {"type" : "string" },
    "column_name"     : {"type" : "string" },
    "preference_name" : {"type" : "string" },
    "language"        : {"type" : "string" } },
  "additionalProperties" : false,
  "required" : [ "table_name", "column_name", "preference_name",
"language" ]
}
```

– SCHEMA_TEXT

```
{ "title": "utl_to_text",
  "description": "To text parameters",
  "type" : "object",
  "properties" : {
    "plaintext"       : {"type" : "boolean" },
    "charset"         : {"type" : "string", "enum" :
[ "UTF8" ] } },
  "additionalProperties": false
}
```

– SCHEMA_DBEMB

```
{ "title" : "utl_to_embedding",
  "description" : "To DB embeddings parameters",
  "type" : "object",
  "properties" : {
    "provider"  : {"type" : "string" },
    "model"     : {"type" : "string" } },
  "additionalProperties": true,
  "required" : [ "provider", "model" ]
}
```

– SCHEMA_SUM

```
{ "title" : "utl_to_summary",
  "description" : "To summary parameters",
  "type" : "object",
  "properties" : {
    "provider"      : {"type" : "string" },
    "numParagraphs" : {"type" : "number" },
    "language"      : {"type" : "string" },
    "glevel"          : {"type" : "string" }
   },
  "additionalProperties" : true,
  "required" : [ "provider" ]
}
```

- **For REST Providers**:

  SCHEMA_REST

  ```
  {  "title" : "REST parameters",
     "description" : "REST versions of utl_to_embedding, utl_to_summary, 
  utl_to_generate_text",
     "type" : "object",
     "properties" : {
       "provider"          : {"type" : "string" },
       "credential_name"   : {"type" : "string" },
       "url"               : {"type" : "string" },
       "model"             : {"type" : "string" }
      },
     "additionalProperties" : true,
     "required" : [ "provider", "credential_name", "url", "model" ] }
  ```

  Note that all the REST calls to third-party service providers share the same schema for their respective embedding, summarization, and text generation operations.

Examples:

- To validate your JSON data against JSON schema, use the PL/SQL function or procedure `DBMS_JSON_SCHEMA.is_valid()`.

  The function returns `1` for valid and `0` for invalid (invalid data can optionally raise an error). The procedure returns `TRUE` for valid and `FALSE` for invalid as the value of an `OUT` parameter.

  ```
  l_valid := sys.DBMS_JSON_SCHEMA.is_valid(params, json(SCHEMA), 
  dbms_json_schema.RAISE_ERROR);
  ```

- To read a detailed validation report of errors, use the PL/SQL procedure `DBMS_JSON_SCHEMA.validate_report`.

  This use of the procedure checks data against schema, providing output in parameters validity (`BOOLEAN`) and errors (`JSON`).

  ```
  sys.DBMS_JSON_SCHEMA.is_valid(params, json(SCHEMA), l_valid, l_errors);
  ```

- If you use the procedure (not function) `is_valid`, then you have access to the validation errors report as an `OUT` parameter. If you use the function `is_valid`, then you do not have access to such a report. Instead of using the function `is_valid`, you can use the PL/SQL function `DBMS_JSON_SCHEMA.validate_report` in a SQL query to validate and return the same full validation information that the reporting `OUT` parameter of the procedure `is_valid` provides, as a JSON type instance.

```
SELECT
JSON_SERIALIZE(DBMS_JSON_SCHEMA.validate_report('json',SCHEMA)
returning varchar2 PRETTY);
```

Related Topics

- DBMS_VECTOR
- DBMS_VECTOR_CHAIN
- DBMS_JSON_SCHEMA

Vector Generation Examples

Review these examples to see how you can generate vectors within and outside the database.

- Generate Embeddings: SQL and PL/SQL Examples
  In these examples, you can see how to generate one or more vector embeddings from text strings and PDF documents.
- Perform Text Processing: PL/SQL Examples
  In these examples, you can see how to use some of the text processing features enabled by Oracle Text.
- Perform Chunking: SQL and PL/SQL Examples
  In these examples, you can see how to extract chunks from text strings and PDF documents.
- Generate Text for a Prompt: PL/SQL Example
  In this example, you can see how to generate text for a given prompt by accessing third-party text generation models.

Generate Embeddings: SQL and PL/SQL Examples

In these examples, you can see how to generate one or more vector embeddings from text strings and PDF documents.

- Convert Text String to Embedding
  You can vectorize text strings like this for chatbots or information-retrieval applications, where you want to directly convert a user's input text to a query vector and then run it against vector index for a fast similarity search.
- Convert File to Text to Chunks to Embeddings
  You can run parallel or step-by-step transformations like this for standalone applications where you want to review, inspect, and accordingly amend results at each stage and then proceed further.
- Convert File to Embeddings
  You can directly extract vector embeddings from a PDF document, using a single-step statement.
- Generate and Use Embeddings for End-to-End Search
  In this example, you first generate embeddings from textual content by using an ONNX model, and then populate and query a vector index. At query time, you also vectorize the query criteria on the fly.

Convert Text String to Embedding

You can vectorize text strings like this for chatbots or information-retrieval applications, where you want to directly convert a user's input text to a query vector and then run it against vector index for a fast similarity search.

You can perform a text-to-embedding transformation using the `UTL_TO_EMBEDDING` PL/SQL API (note the singular "embedding") or the `VECTOR_EMBEDDING` SQL function. Both `UTL_TO_EMBEDDING` and `VECTOR_EMBEDDING` directly return a `VECTOR` type (not an array).

Determine which API to use:

- If you want to access a third-party embedding model, then you can use `UTL_TO_EMBEDDING` from either the `DBMS_VECTOR` or `DBMS_VECTOR_CHAIN` package.

  This scenario uses the `DBMS_VECTOR.UTL_TO_EMBEDDING` API.
- If you are using an ONNX format embedding model, then you can use both `VECTOR_EMBEDDING` and `UTL_TO_EMBEDDING`.

To generate a vector embedding with "`hello`" as the input:

1. Start SQL*Plus and connect to Oracle Database as a local test user.
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba
      ```

      ```
      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

   b. Create a local test user (`docuser`) and grant necessary privileges:

      ```
      DROP USER docuser cascade;
      ```

      ```
      CREATE USER docuser identified by docuser DEFAULT TABLESPACE tbs1
      quota unlimited on tbs1;
      ```

      ```
      GRANT DB_DEVELOPER_ROLE, create credential to docuser;
      ```

   c. Connect to Oracle Database as the test user and alter the environment settings for your session:

      ```
      CONN docuser/password@CDB_PDB
      ```

      ```
      SET ECHO ON
      SET FEEDBACK 1
      SET NUMWIDTH 10
      SET LINESIZE 80
      ```

```
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

d. Set the HTTP proxy server, if configured:

```
EXEC UTL_HTTP.SET_PROXY('<proxy-hostname>:<proxy-port>');
```

e. Grant connect privilege for a host using the `DBMS_NETWORK_ACL_ADMIN` procedure. This example uses `*` to allow any host. However, you can explicitly specify each host that you want to connect to.

```
BEGIN
  DBMS_NETWORK_ACL_ADMIN.APPEND_HOST_ACE(
    host => '*',
    ace => xs$ace_type(privilege_list => xs$name_list('connect'),
                       principal_name => 'docuser',
                       principal_type => xs_acl.ptype_db));
END;
/
```

2. If you are using a third-party embedding model and need to make a REST call, set up your credentials for the REST provider and then call `UTL_TO_EMBEDDING`.

- **Using Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI**:

  a. Run `DBMS_VECTOR.CREATE_CREDENTIAL` to create and store a credential.

  Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI require the following authentication parameter:

  ```
  { "access_token": "<access token>" }
  ```

  You will later refer to this credential name when declaring JSON parameters for the `UTL_to_EMBEDDING` call.

  ```
  exec dbms_vector.drop_credential('<credential name>');


  declare
    jo json_object_t;
  begin
    jo := json_object_t();
    jo.put('access_token', '<access token>');
    dbms_vector.create_credential(
      credential_name    => '<credential name>',
      params             => json(jo.to_string));
  end;
  /
  ```

  Replace the `access_token` and `credential_name` values. For example:

  ```
  declare
    jo json_object_t;
  begin
  ```

```
  jo := json_object_t();
  jo.put('access_token', 'AbabA1B123aBc123AbabAb123a1a2ab');
  dbms_vector.create_credential(
    credential_name   => 'HF_CRED',
    params            => json(jo.to_string));
end;
/
```

b. Call `DBMS_VECTOR.UTL_TO_EMBEDDING`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for embedding service>",
  "model": "<embedding model name>"
}';

select dbms_vector.utl_to_embedding('hello', json(:params)) from
dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  v vector;
begin
  input := 'hello';

  params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for embedding service>",
  "model": "<embedding model name>"
}';

  v := dbms_vector.utl_to_embedding(input, json(params));
  dbms_output.put_line(vector_serialize(v));
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `provider`, `credential_name`, `url`, and `model` values. Optionally, you can specify additional REST provider parameters.

Cohere example:

```
{
  "provider": "cohere",
  "credential_name": "COHERE_CRED",
  "url": "https://api.cohere.example.com/embed",
  "model": "embed-model",
  "input_type": "search_query"
}
```

Google AI example:

```
{
  "provider": "googleai",
  "credential_name": "GOOGLEAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "embed-model"
}
```

Hugging Face example:

```
{
  "provider": "huggingface",
  "credential_name": "HF_CRED",
  "url": "https://api.huggingface.example.com/",
  "model": "embed-model",
  "wait_for_model": "true"
}
```

OpenAI example:

```
{
  "provider": "openai",
  "credential_name": "OPENAI_CRED",
  "url": "https://api.openai.example.com/embeddings",
  "model": "embed-model"
}
```

Vertex AI example:

```
{
  "provider": "vertexai",
  "credential_name": "VERTEXAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "embed-model"
}
```

- **Using Generative AI**:

  a. Run `DBMS_VECTOR.CREATE_CREDENTIAL` to create and store an OCI credential (`OCI_CRED`).

Generative AI requires the following authentication parameters:

```
{
"user_ocid": "<user ocid>",
"tenancy_ocid": "<tenancy ocid>",
"compartment_ocid": "<compartment ocid>",
"private_key": "<private key>",
"fingerprint": "<fingerprint>"
}
```

You will later refer to this credential name when declaring JSON parameters for the `UTL_to_EMBEDDING` call.

> **Note:**
>
> The generated private key may appear as:
>
> ```
> -----BEGIN RSA PRIVATE KEY-----
> <private key string>
> -----END RSA PRIVATE KEY-----
> ```
>
> You pass the *`<private key string>`* value (excluding the `BEGIN` and `END` lines), either as a single line or as multiple lines.

```
exec dbms_vector.drop_credential('OCI_CRED');


declare
  jo json_object_t;
begin
  jo := json_object_t();
  jo.put('user_ocid','<user ocid>');
  jo.put('tenancy_ocid','<tenancy ocid>');
  jo.put('compartment_ocid','<compartment ocid>');
  jo.put('private_key','<private key>');
  jo.put('fingerprint','<fingerprint>');
  dbms_output.put_line(jo.to_string);
  dbms_vector.create_credential(
    credential_name   => 'OCI_CRED',
    params            => json(jo.to_string));
end;
/
```

Replace all the authentication parameter values. For example:

```
declare
  jo json_object_t;
begin
  jo := json_object_t();
```

```
jo.put('user_ocid','ocid1.user.oc1..aabbalbbaa1112233aabbaabb
1111222aa1111bb');

jo.put('tenancy_ocid','ocid1.tenancy.oc1..aaaaalbbbb1112233aa
aabbaa1111222aaa111a');

jo.put('compartment_ocid','ocid1.compartment.oc1..ababalabab1
112233abababab1111222aba11ab');

jo.put('private_key','AAAaaaBBB11112222333...AAA111AAABBB222a
aa1a/+');

jo.put('fingerprint','01:1a:a1:aa:12:a1:12:1a:ab:12:01:ab:a1:
12:ab:1a');
  dbms_output.put_line(jo.to_string);
  dbms_vector.create_credential(
    credential_name    => 'OCI_CRED',
    parameters         => json(jo.to_string));
end;
/
```

b. Call `DBMS_VECTOR.UTL_TO_EMBEDDING`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for embedding service>",
  "model": "<REST provider embedding model name>"
}';

select dbms_vector.utl_to_embedding('hello', json(:params))
from dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  v vector;
begin
  input := 'hello;

  params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for embedding service>",
  "model": "<REST provider embedding model name>"
}';

  v := dbms_vector.utl_to_embedding(input, json(params));
  dbms_output.put_line(vector_serialize(v));
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `url` and `model` values. Optionally, you can specify additional REST provider-specific parameters.

For example:

```
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "https://generativeai.oci.example.com/embedText",
  "model": "embed-modelname",
  "batch_size": 10
}
```

3. If you are using a declared embedding model, then call either `VECTOR_EMBEDDING` or `UTL_TO_EMBEDDING`.
   a. Load your ONNX model into Oracle Database.

      For detailed information on how to perform this step, see Import ONNX Models and Generate Embeddings.

      Here, `doc_model` specifies the name under which the imported model is stored in Oracle Database.
   b. Call `VECTOR_EMBEDDING` or `UTL_TO_EMBEDDING`:
      - `VECTOR_EMBEDDING`:

        ```
        SELECT TO_VECTOR(VECTOR_EMBEDDING(doc_model USING 'hello' as
        data)) AS embedding;
        ```
      - `DBMS_VECTOR.UTL_TO_EMBEDDING`:

        ```
        var params clob; exec :params := '{"provider":"database",
        "model":"doc_model"}';

        select dbms_vector.utl_to_embedding('hello', json(:params)) from
        dual;
        ```

   The generated embedding appears as follows:

   ```
   EMBEDDING
   ------------------------------------------------------------------------
   -----------------------------------------------------------
   [8.78423732E-003,-4.29633334E-002,-5.93001908E-003,-4.65480909E-002,2.1433
   3013E-002,6.53376281E-002,-5.93746938E-002,2.10403297E-002,
   4.38376889E-002,5.22960871E-002,1.25104953E-002,6.49512559E-002,-9.2699807
   1E-003,-6.97442219E-002,-3.02916039E-002,-4.74979728E-003,
   ```

```
-1.08755399E-002,-4.63751052E-003,3.62781435E-002,-9.35919806E-002,-
1.13934642E-002,-5.74270077E-002,-1.36667723E-002,2.42995787E-002,
-6.96804151E-002,4.93822657E-002,1.01460628E-002,-1.56464987E-002,-2
.39410568E-002,-4.27529104E-002,-5.65665103E-002,-1.74160264E-002,
5.05326502E-002,4.31500375E-002,-2.6994409E-002,-1.72731467E-002,9.3
0535868E-002,6.85951149E-004,5.61876409E-003,-9.0233935E-003,
-2.55788807E-002,-2.04174276E-002,3.74175981E-002,-1.67872179E-002,1
.07479304E-001,-6.64602639E-003,-7.65537247E-002,-9.71965566E-002,
-3.99636962E-002,-2.57076006E-002,-5.62455431E-002,-1.3583754E-001,3
.45946029E-002,1.85191762E-002,3.01524661E-002,-2.62163244E-002,
-4.05582506E-003,1.72979087E-002,-3.66434865E-002,-1.72491539E-002,3
.95228416E-002,-1.05518714E-001,-1.27463877E-001,1.42578809E-002
```

This example uses the default settings for each provider. For detailed information on additional parameters, refer to your third-party provider's documentation.

Related Topics

- UTL_TO_EMBEDDING
- VECTOR_EMBEDDING

Convert File to Text to Chunks to Embeddings

You can run parallel or step-by-step transformations like this for standalone applications where you want to review, inspect, and accordingly amend results at each stage and then proceed further.

Using a set of functions from the `DBMS_VECTOR_CHAIN` package, you first convert a PDF file to text (`UTL_TO_TEXT`), split the text into chunks (`UTL_TO_CHUNKS`), and then create vector embeddings on each chunk (`UTL_TO_EMBEDDINGS`).

To generate embeddings using a declared embedding model, through step-by-step transformation chains:

1. Start SQL*Plus and connect to Oracle Database as a local test user:
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba


      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

b. Create a local test user (`docuser`) and grant necessary privileges:

```
drop user docuser cascade;


create user docuser identified by docuser DEFAULT TABLESPACE tbs1
quota unlimited on tbs1;


grant DB_DEVELOPER_ROLE to docuser;
```

c. Create a local directory on your server (`VEC_DUMP`) to store your input data and model files. Grant necessary privileges:

```
create or replace directory VEC_DUMP as '/my_local_dir/';


grant read, write on directory VEC_DUMP to docuser;

commit;
```

d. Connect to Oracle Database as the test user and alter the environment settings for your session:

```
conn docuser/password@CDB_PDB;

SET ECHO ON
SET FEEDBACK 1
SET NUMWIDTH 10
SET LINESIZE 80
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

2. Convert file to text:

a. Create a relational table (`documentation_tab`) and store your PDF document (*Oracle Database Concepts*) in it:

```
drop table documentation_tab purge;


CREATE TABLE documentation_tab (id number, data blob);

INSERT INTO documentation_tab values(1, to_blob(bfilename('VEC_DUMP',
'database-concepts23ai.pdf')));

commit;


SELECT dbms_lob.getlength(t.data) from documentation_tab t;
```

b. Run `UTL_TO_TEXT` to convert the PDF document into text format:

```
SELECT dbms_vector_chain.utl_to_text(dt.data) from
documentation_tab dt;
```

An excerpt from the output is as follows:

```
DBMS_VECTOR_CHAIN.UTL_TO_TEXT(DT.DATA)
--------------------------------------------------------------------
------
Database Concepts
23ai
Oracle Database Database Concepts, 23ai

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```

```
Data Access

1 row selected.
```

3. Convert text to chunks:

   a. Run `UTL_TO_CHUNKS` to chunk the text document:

```
SELECT ct.*
  from documentation_tab dt,

dbms_vector_chain.utl_to_chunks(dbms_vector_chain.utl_to_text(dt.data)
) ct;
```

An excerpt from the output is as follows:

```
{"chunk_id":1,"chunk_offset":1508024,"chunk_length":579,"chunk_data":"
Inventory
\n\n\n\nAnalysis \n\n\n\nReporting \n\n\n\nMining\n\n\n\nSummary
\n\n\n\nData
 \n\n\n\nRaw Data\n\n\n\nMetadata\n\n\n\nSee Also:\n\n\n\nOracle
Database Data
Warehousing Guide to learn about transformation
\n\n\n\nmechanisms\n\n\n\nOvervie
w of Extraction, Transformation, and Loading (ETL) \n\n\n\nThe
process of extrac
ting data from source systems and bringing it into the warehouse is
\n\n\n\ncomm
only called ETL: extraction, transformation, and loading. ETL refers
to a broad
process \n\n\n\nrather than three well-defined steps.\n\n\n\nIn a
typical scenar
io, data from one or more operational systems is extracted and then"}

{"chunk_id":2,"chunk_offset":1508603,"chunk_length":607,"chunk_data":"
physica
lly transported to the target system or an intermediate system for
processing. \
n\n\n\nDepending on the method of transportation, some
transformations can occur
 during this \n\n\n\nprocess. For example, a SQL statement that
directly accesse
s a remote target through a \n\n\n\ngateway can concatenate two
columns as part
of the \n\n\n\nSELECT\n\n\n\nstatement. \n\n\n\nOracle Database is
not itself an
 ETL tool. However, Oracle Database provides a rich set of
\n\n\n\ncapabilities
usable by ETL tools and customized ETL solutions. ETL capabilities
provided by \
n\n\n\nOracle Database include:\n\n\n\n? \n\n\n\nTransportable
tablespaces"}

3728 rows selected.
```

Notice the extra spaces and newline characters (`\n\n`) in the chunked output. You can set the `normalize` chunking parameter to omit duplicate characters, extra spaces, or newline characters from the output. You can further refine your chunks by applying other chunking specifications, such as split conditions or maximum size limits.

b. Supply the following JSON parameters to use normalization and some of the custom chunking specifications:

```
SELECT ct.*
  from documentation_tab dt,
  dbms_vector_chain.utl_to_chunks(dbms_vector_chain.utl_to_text(
    dt.data),
    JSON('{
           "by" : "words",
           "max" : "100",
           "overlap" : "0",
           "split" : "recursively",
           "language" : "american",
           "normalize" : "all"
          }')) ct;
```

The output may now appear as:

```
{"chunk_id":2536,"chunk_offset":1372527,"chunk_length":633,"chunk
_data":"The dat
abase maps granules to parallel execution servers at execution
time. When a para
llel execution server finishes reading the rows corresponding to
a granule, and
when granules remain, it obtains another granule from the query
coordinator. This
operation continues until the table has been read. The execution
servers send
results back to the coordinator, which assembles the pieces into
the desired full
table scan. Oracle Database VLDB and Partitioning Guide to learn
how to use
parallel execution. Oracle Database Data Warehousing Guide to
learn about
recommended"}

{"chunk_id":2537,"chunk_offset":1373160,"chunk_length":701,"chunk
_data":"initial
ization parameters for parallelism\n\nChapter 18\n\nOverview of
Background Proce
sses\n\nApplication and Oracle Net Services Architecture\n\nThis
chapter defines
application architecture and describes how an Oracle database
and database appli
cations work in a distributed processing environment. This
material applies to
almost every type of Oracle Database environment. Overview of
Oracle Application
Architecture In the context of this chapter, application
architecture refers to
the computing environment in which a database application connects to
an Oracle
database."}

3728 rows selected.
```

The chunking results contain:

- `chunk_id`: Chunk ID for each chunk
- `chunk_offset`: Original position of each chunk in the source document, relative to the start of document (which has a position of `1`)
- `chunk_length`: Character length of each chunk
- `chunk_data`: Text pieces from each chunk

4. Convert chunks to embeddings:

   a. Drop and load your ONNX model by calling the `load_onnx_model` procedure.

```
EXECUTE dbms_vector.drop_onnx_model(model_name => 'doc_model', force
=> true);


EXECUTE dbms_vector.load_onnx_model('VEC_DUMP',
'my_embedding_model.onnx', 'doc_model', JSON('{"function" :
"embedding", "embeddingOutput" : "embedding" , "input": {"input":
["DATA"]}}'));
```

   Replace `my_embedding_model.onnx` with an ONNX export of your embedding model. Here, `doc_model` specifies the name under which the imported model is stored in Oracle Database.

   Note:

   If you do not have an embedding model in ONNX format, then perform the steps listed in Convert Pretrained Models to ONNX Format.

   b. Declare embedding parameters:

```
var embed_params clob;

exec :embed_params := '{"provider":"database", "model":"doc_model"}';
```

   c. Run `UTL_TO_EMBEDDINGS` to generate a set of vector embeddings corresponding to the chunks:

```
SELECT et.* from
  documentation_tab dt,
  dbms_vector_chain.utl_to_embeddings(

dbms_vector_chain.utl_to_chunks(dbms_vector_chain.utl_to_text(dt.data)
),
    json(:embed_params)) et;
```

An excerpt from the output is as follows:

```
{"embed_id":"1","embed_data":"Introduction to Oracle
Database\n\n\nThis
chapter provides an overview of Oracle Database. Every organization
has informat
ion that it must store and manage to meet its requirements. For
example, a corpo
ration must collect and maintain human resources records for its
employees. About
Relational Databases and Schema Objects\n\n\nData Access tables
with parent keys,
base, upgrade, UROWID data type, user global area (UGA), user
program interface,
","embed_vector":"[0.111119926,0.0423980951,-0.00929224491,-0.035241
1047,-0.0144
591287,0.0277361721,0.183199733,-0.0245029964,-0.137614027,0.0730137
378,0.017934
6036,0.0788726509,0.0176453814,0.100403085,-0.0518687107,-0.01526450
27,0.0283792
187,-0.114087239,0.0139923804,0.0747490972,-0.181839675,-0.130034953
,0.101207718
,0.117135495,-0.0682030097,-0.217743069,0.0613380745,0.0150767341,0.
0361393057,-
0.113082513,-0.0550440662,-0.000983044971,-0.00719357422,0.1590323,-
0.0220414512
,-0.0723528489,-0.0126240514,-0.175765082,0.168952227,0.0466451086,-
0.12136507,-
0.0442310236,0.0139067639,0.054659389,-0.29653421,-0.0988782048,0.07
94349238,-0.
0758788213,0.0152856084,-0.0260562375,0.0652966872,-0.0782724097,-0.
0226081386,0
.0909011662,-0.184569761,0.159565002,-0.15350005,-0.0108382348,0.101
788878,1.919
59683E-002,2.54665539E-002,2.50248201E-002,5.29858321E-002,1.4235953
8E-002,5.655
82886E-002,3.41602638E-002,3.18607911E-002,-3.07250433E-002,-3.60006
578E-002,-3.
26940455E-002,-5.13980947E-002,-9.18597169E-003,-2.40122043E-002,2.1
5246622E-002
,-3.89301814E-002,1.09825116E-002,-8.59739035E-002,-3.34327705E-002,
-6.52310252E
-002,2.46418975E-002,6.27725571E-003,6.54156879E-002,-2.97986511E-00
3,-1.485541E
-003,-9.00155635E-003]"}

{"embed_id":2,"embed_data":"1-18 Database, 19-6 write-ahead,18-17
Learn session
memory in a large pool. The multitenant architecture enables an
Oracle database
to function as a multitenant container database (CDB).
XStream,20-38\nZero Data
Loss Recovery Appliance See Recovery Appliance zone maps, An application
contai
ner consists of exactly one application root, and PDBs plugged in to this
root.
Index-21\n D:20231208125114-08'00' D:20231208125114-08'00'
D:20231208125114-08'0
0'
19-6","embed_vector":"[6.30229115E-002,6.80943206E-002,-6.94655553E-002,-2
.58
157589E-002,-1.89648587E-002,-9.02655348E-002,1.97774544E-002,-9.39233322E
-003,-
5.06882742E-002,2.0078931E-002,-1.28898735E-003,-4.10606936E-002,2.0983121
4E-003
,-4.53372523E-002,-7.09890276E-002,5.38906306E-002,-5.81014939E-002,-1.395
9175E-
004,-1.08725717E-002,-3.79145369E-002,-4.39973129E-003,3.25602405E-002,6.5
887302
2E-002,-4.27212603E-002,-3.00925318E-002,3.07144262E-002,-2.26370787E-004,
-4.623
15865E-002,1.11807801E-001,7.36674219E-002,-1.61244173E-003,7.35205635E-00
2,4.16
726843E-002,-5.08309156E-002,-3.55720241E-003,4.49763797E-003,5.03803678E-
002,2.
32542045E-002,-2.58533042E-002,9.06257033E-002,8.49585086E-002,8.65213498E
-002,5
.84013164E-002,-7.72946924E-002,6.65430725E-002,-1.64568517E-002,3.2397888
6E-002
,2.24988302E-003,3.02566844E-003,-2.43405364E-002,9.75424573E-002,4.146305
38E-00
3,1.89351812E-002,-1.10467218E-001,-1.24333188E-001,-2.36738548E-002,7.542
77706E
-002,-1.64660662E-002,-1.38906585E-002,3.42438952E-003,-1.88432514E-005,-2
.47511
379E-002,-3.42802797E-003,3.23110656E-003,4.24311385E-002,6.59448802E-002,
-3.311
67318E-002,-5.14010936E-002,2.38897409E-002,-9.00154635E-002]"}

3728 rows selected.
```

The embedding results contain:

- `embed_id`: ID number of each vector embedding
- `embed_data`: Input text that is transformed into embeddings
- `embed_vector`: Generated vector representations

Related Topics

- DBMS_VECTOR Package
- DBMS_VECTOR_CHAIN Package

Convert File to Embeddings

You can directly extract vector embeddings from a PDF document, using a single-step statement.

Perform a file-to-text-to-chunks-to-embeddings transformation (using a declared embedding model), by calling a set of `DBMS_VECTOR_CHAIN.UTL` functions in a single `CREATE TABLE` statement.

This statement creates a relational table (`doc_chunks`) from unstructured text chunks and the corresponding vector embeddings:

```
CREATE TABLE doc_chunks as
(select dt.id doc_id, et.embed_id, et.embed_data,
to_vector(et.embed_vector) embed_vector
 from
   documentation_tab dt,
   dbms_vector_chain.utl_to_embeddings(

dbms_vector_chain.utl_to_chunks(dbms_vector_chain.utl_to_text(dt.data),
 json('{"normalize":"all"}')),
       json('{"provider":"database", "model":"doc_model"}')) t,
   JSON_TABLE(t.column_value, '$[*]' COLUMNS (embed_id NUMBER PATH
'$.embed_id', embed_data VARCHAR2(4000) PATH '$.embed_data',
embed_vector CLOB PATH '$.embed_vector')) et
);
```

Note that each successive function depends on the output of the previous function, so the order of chains is important here. First, the output from `utl_to_text` (`dt.data` column) is passed as an input for `utl_to_chunks` and then the output from `utl_to_chunks` is passed as an input for `utl_to_embeddings`.

For complete example, run SQL Quick Start, where you embed two Oracle Database Documentation books in the `doc_chunks` table and perform similarity searches using vector indexes.

Generate and Use Embeddings for End-to-End Search

In this example, you first generate embeddings from textual content by using an ONNX model, and then populate and query a vector index. At query time, you also vectorize the query criteria on the fly.

This example covers the entire workflow of Oracle AI Vector Search, as described in Understand the Stages of Data Transformations. If you are not yet familiar with the concepts beyond generating embeddings (such as creating and querying vector indexes), review the remaining sections before running this scenario.
To run an end-to-end similarity search workflow using a declared embedding model:

1. Start SQL*Plus and connect to Oracle Database as a local test user:

a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

```
conn sys/password@CDB_PDB as sysdba


CREATE TABLESPACE tbs1
DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
EXTENT MANAGEMENT LOCAL
SEGMENT SPACE MANAGEMENT AUTO;
```

b. Create a local test user (`docuser`) and grant necessary privileges:

```
drop user docuser cascade;


create user docuser identified by docuser DEFAULT TABLESPACE tbs1
quota unlimited on tbs1;


grant DB_DEVELOPER_ROLE to docuser;
```

c. Create a local directory on your server (`VEC_DUMP`) to store your input data and model files. Grant necessary privileges:

```
create or replace directory VEC_DUMP as '/my_local_dir/';


grant read, write on directory VEC_DUMP to docuser;

commit;
```

d. Connect to Oracle Database as the test user and alter the environment settings for your session:

```
conn docuser/password@CDB_PDB;

SET ECHO ON
SET FEEDBACK 1
SET NUMWIDTH 10
SET LINESIZE 80
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

2. Create a relational table (`documentation_tab`) and store your textual content in it.

```
drop table documentation_tab purge;


create table documentation_tab (id number, text clob);


insert into documentation_tab values (1,
    'Analytics empowers business analysts and consumers with
modern, AI-powered, self-service analytics capabilities for data
preparation, visualization, enterprise reporting, augmented
analysis, and natural language processing.
     Oracle Analytics Cloud is a scalable and secure public cloud
service that provides capabilities to explore and perform
collaborative analytics for you, your workgroup, and your
enterprise.

     Oracle Analytics Cloud is available on Oracle Cloud
Infrastructure Gen 2 in several regions in North America, EMEA,
APAC, and LAD when you subscribe through Universal Credits. You can
subscribe to Professional Edition or Enterprise Edition.');

insert into documentation_tab values (3,
    'Generative AI Data Science is a fully managed and serverless
platform for data science teams to build, train, and manage machine
learning models in the Oracle Cloud Infrastructure.');

insert into documentation_tab values (4,
    'Language allows you to perform sophisticated text analysis at
scale. Using the pretrained and custom models, you can process
unstructured text to extract insights without data science
expertise.
     Pretrained models include sentiment analysis, key phrase
extraction, text classification, and named entity recognition. You
can also train custom models for named entity recognition and text
     classification with domain specific datasets. Additionally,
you can translate text across numerous languages.');

insert into documentation_tab values (5,
    'When you work with Oracle Cloud Infrastructure, one of the
first steps is to set up a virtual cloud network (VCN) for your
cloud resources. This topic gives you an overview of Oracle Cloud
     Infrastructure Networking components and typical scenarios for
using a VCN. A virtual, private network that you set up in Oracle
data centers. It closely resembles a traditional network, with
     firewall rules and specific types of communication gateways
that you can choose to use. A VCN resides in a single Oracle Cloud
Infrastructure region and covers one or more CIDR blocks
     (IPv4 and IPv6, if enabled). See Allowed VCN Size and Address
Ranges. The terms virtual cloud network, VCN, and cloud network are
used interchangeably in this documentation.
     For more information, see VCNs and Subnets.');

insert into documentation_tab values (6,
    'NetSuite banking offers several processing options to accurately
track your income. You can record deposits to your bank accounts to
capture customer payments and other monies received in the
     course of doing business. For a deposit, you can select payments
received for existing transactions, add funds not related to transaction
payments, and record any cash received back from the bank.');

commit;
```

3. Load your ONNX model by calling the `load_onnx_model` procedure.

   ```
   EXECUTE dbms_vector.drop_onnx_model(model_name => 'doc_model', force =>
   true);


   EXECUTE dbms_vector.load_onnx_model(
      'VEC_DUMP',
      'my_embedding_model.onnx',
      'doc_model',
      json('{"function" : "embedding", "embeddingOutput" : "embedding" ,
   "input": {"input": ["DATA"]}}')
   );
   ```

   Replace `my_embedding_model.onnx` with an ONNX export of your embedding model. Here, `doc_model` specifies the name under which the imported model is stored in Oracle Database.

   Note:

   If you do not have an embedding model in ONNX format, then perform the steps listed in Convert Pretrained Models to ONNX Format.

4. Create a relational table (`doc_chunks`) to store unstructured data chunks and associated vector embeddings, by using `doc_model`.

   ```
   create table doc_chunks as (
     SELECT d.id id,
            row_number() over (partition by d.id order by d.id) chunk_id,
            vc.chunk_offset chunk_offset,
            vc.chunk_length chunk_length,
            vc.chunk_text chunk,
            vector_embedding(doc_model using vc.chunk_text as data) vector
     FROM documentation_tab d,
          vector_chunks(d.text by words max 100 overlap 10 split
   RECURSIVELY) vc
   );
   ```

   The `CREATE TABLE` statement reads the text from the `DOCUMENTATION_TAB` table, first applies the `VECTOR_CHUNKS` SQL function to split the text into chunks based on the specified chunking parameters, and then applies the `VECTOR_EMBEDDING` SQL function to generate corresponding vector embedding on each resulting chunk text.

5. Explore the `doc_chunks` table by selecting rows from it to see the chunked output.

```
desc doc_chunks;
set linesize 100
set long 1000
col id for 999
col chunk_id for 99999
col chunk_offset for 99999
col chunk_length for 99999
col chunk for a30
col vector for a100


select id, chunk_id, chunk_offset, chunk_length, chunk from
doc_chunks;
```

The chunking output returns a set of seven chunks, which are split recursively, that is, using the `BLANKLINE`, `NEWLINE`, `SPACE`, `NONE` sequence. Note that Document 5 produces two chunks when the maximum word limit of `100` is reached.

You can see that the first chunk ends at a blank line. The text from the first chunk overlaps onto the second chunk, that is, 10 words (including comma and period; underlined below) are overlapping. Similarly, there is an overlap of 10 (also underlined below) between the fifth and sixth chunks.

```
  ID CHUNK_ID CHUNK_OFFSET CHUNK_LENGTH CHUNK
---- -------- ------------ ------------
------------------------------
   1     1         1       418  Analytics empowers business an
                          alysts and consumers with mode
                          rn, AI-powered, self-service a
                          nalytics capabilities for data
                          preparation, visualization, e
                          nterprise reporting, augmented
                          analysis, and natural languag
                          e processing.
                          Oracle Analytics Cloud is
                          a scalable and secure public
                          cloud service that provides ca
                          pabilities to explore and perf
                          orm collaborative analytics for
                          you, your workgroup, and your
                          enterprise.

   1     2         373      291 for you, your workgroup, and
                          your enterprise.
                          Oracle Analytics Cloud is
                          available on Oracle Cloud Inf
                          rastructure Gen 2 in several r
                          egions in North America, EMEA,
                          APAC, and LAD when you subscr
                          ibe through Universal Credits.
                          You can subscribe to Professi
```

```
                                    onal Edition or Enterprise Edi
                                    tion.

3      1         1     180  Generative AI Data Science is
                                    a fully managed and serverless
                                    platform for data science tea
                                    ms to build, train, and manage
                                    machine learning models in th
                                    e Oracle Cloud Infrastructure.

4      1         1     505  Language allows you to perform
                                    sophisticated text analysis a
                                    t scale. Using the pretrained
                                    and custom models, you can pro
                                    cess unstructured text to extr
                                    act insights without data scie
                                    nce expertise.
                                    Pretrained models include
                                    sentiment analysis, key phras
                                    e extraction, text classificat
                                    ion, and named entity recognit
                                    ion. You can also train custom
                                    models for named entity recog
                                    nition and text
                                    classification with domai
                                    n specific datasets. Additiona
                                    lly, you can translate text ac
                                    ross numerous languages.

5      1         1     386  When you work with Oracle Clou
                                    d Infrastructure, one of the f
                                    irst steps is to set up a virt
                                    ual cloud network (VCN) for yo
                                    ur cloud resources. This topic
                                    gives you an overview of Orac
                                    le Cloud
                                    Infrastructure Networking
                                    components and typical scenar
                                    ios for using a VCN. A virtual
                                    , private network that you set
                                    up in Oracle data centers. It
                                    closely resembles a tradition
                                    al network, with

5      2          329     474  centers. It closely resembles
                                    a traditional network, with
                                    firewall rules and specif
                                    ic types of communication gate
                                    ways that you can choose to us
                                    e. A VCN resides in a single O
                                    racle Cloud Infrastructure reg
                                    ion and covers one or more CID
                                    R blocks
                                    (IPv4 and IPv6, if enable
                                    d). See Allowed VCN Size and A
```

```
                                   ddress Ranges. The terms virtu
                                   al cloud network, VCN, and clo
                                   ud network are used interchang
                                   eably in this documentation.
                                   For more information, see
                                   VCNs and Subnets.

   6     1        1      393  NetSuite banking offers severa
                                 l processing options to accura
                                 tely track your income. You ca
                                 n record deposits to your bank
                                 accounts to capture customer
                                 payments and other monies rece
                                 ived in the
                                 course of doing business.
                                 For a deposit, you can select
                                 payments received for existin
                                 g transactions, add funds not
                                 related to transaction payment
                                 s, and record any cash receive
                                 d back from the bank.

7 rows selected.
```

6. Explore the first vector result by selecting rows from the `doc_chunks` table to see the embedding output.

```
select vector from doc_chunks where rownum <= 1;
```

An excerpt from the output is as follows:

```
[1.18813422E-002,2.53968383E-003,-5.33896387E-002,1.46877998E-003,5.
77209815E-002,-1.58939194E-002,3
.12595293E-002,-1.13087103E-001,8.5138239E-002,1.10731693E-002,3.706
71228E-002,4.03710492E-002,1.503
95066E-001,3.31836529E-002,-1.98343433E-002,6.16453104E-002,4.282767
7E-002,-4.02921103E-002,-7.84291
551E-002,-4.79201972E-002,-5.06678E-002,-1.36317732E-002,-3.7761624E
-003,-2.3332756E-002,1.42400926E
-002,-1.11553416E-001,-3.70503664E-002,-2.60722954E-002,-1.2074843E-
002,-3.55089158E-002,-1.03518805
E-002,-7.05051869E-002,5.63110895E-002,4.79055084E-002,-1.46315445E-
003,8.83129537E-002,5.12795225E-
002,7.5858552E-003,-4.13030013E-002,-5.2099824E-002,5.75958602E-002,
3.72097567E-002,6.11167103E-002,
,-1.23207876E-003,-5.46219759E-003,3.04734893E-002,1.80617068E-002,-
2.85708476E-002,-1.01670986E-002
,6.49402961E-002,-9.76506807E-003,6.15146831E-002,5.27246818E-002,7.
44994432E-002,-5.86469211E-002,8
.84285953E-004,2.77456306E-002,1.99283361E-002,2.37570312E-002,2.333
89344E-002,-4.07911092E-002,-7.6
1070028E-002,1.23929314E-001,6.65794984E-002,-6.15389943E-002,2.6251
0721E-002,-2.48490628E-002]
```

7. Create an index on top of the `doc_chunks` table's `vector` column.

```
create vector index vidx on doc_chunks (vector)
   organization neighbor partitions
   with target accuracy 95
   distance EUCLIDEAN parameters (
    type IVF,
    neighbor partitions 2);
```

8. Run queries using the vector index.

   - Query about Machine Learning:

```
select id, vector_distance(
    vector,
    vector_embedding(doc_model using 'machine learning models' as
data),
    EUCLIDEAN) results
FROM doc_chunks order by results;



  ID    RESULTS
---- ----------
   3 1.074E+000
   4 1.086E+000
   5 1.212E+000
   5 1.296E+000
   1 1.304E+000
   6 1.309E+000
   1 1.365E+000

7 rows selected.
```

   - Query about Generative AI:

```
select id, vector_distance(
    vector,
    vector_embedding(doc_model using 'gen ai' as data),
    EUCLIDEAN) results
FROM doc_chunks order by results;


  ID    RESULTS
---- ----------
   4 1.271E+000
   3 1.297E+000
   1 1.309E+000
   5  1.32E+000
   1 1.352E+000
   5 1.388E+000
   6 1.424E+000

7 rows selected.
```

- Query about Networks:

```
select id, vector_distance(
  vector,
  vector_embedding(doc_model using 'computing networks' as data),
  MANHATTAN) results
FROM doc_chunks order by results;


  ID    RESULTS
---- ----------
   5 1.387E+001
   5 1.441E+001
   3 1.636E+001
   1 1.707E+001
   4 1.758E+001
   1 1.795E+001
   6 1.902E+001

7 rows selected.
```

- Query about Banking:

```
select id, vector_distance(
    vector,
    vector_embedding(doc_model using 'banking, money' as data),
    MANHATTAN) results
FROM doc_chunks order by results;


  ID    RESULTS
---- ----------
   6 1.363E+001
   1 1.969E+001
   5 1.978E+001
   5 1.997E+001
   3 1.999E+001
   1 2.058E+001
   4 2.079E+001

7 rows selected.
```

Related Topics

- DBMS_VECTOR_CHAIN Package

Perform Text Processing: PL/SQL Examples

In these examples, you can see how to use some of the text processing features enabled by Oracle Text.

- Convert Text String to Summary
  You can extract a concise summary from large and complex documents.

- Create and Use Custom Vocabulary
  You can see how to create and use your own vocabulary of tokens when chunking data.
- Create and Use Custom Language Data
  You can create and use your own language-specific conditions (such as common abbreviations) when chunking data.

Convert Text String to Summary

You can extract a concise summary from large and complex documents.

You can see how to access third-party text summarization models to perform a text-to-summary transformation, by using the `DBMS_VECTOR_CHAIN.UTL_TO_SUMMARY` API.

1. Start SQL*Plus and connect to Oracle Database as a local test user.
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba


      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

   b. Create a local test user (`docuser`) and grant necessary privileges:

      ```
      DROP USER docuser cascade;


      CREATE USER docuser identified by docuser DEFAULT TABLESPACE tbs1
      quota unlimited on tbs1;


      GRANT DB_DEVELOPER_ROLE, create credential to docuser;
      ```

   c. Connect to Oracle Database as the test user and alter the environment settings for your session:

      ```
      CONN docuser/password@CDB_PDB


      SET ECHO ON
      SET FEEDBACK 1
      SET NUMWIDTH 10
      SET LINESIZE 80
      SET TRIMSPOOL ON
      SET TAB OFF
      SET PAGESIZE 10000
      SET LONG 10000
      ```

d. Set the HTTP proxy server if configured:

```
EXEC UTL_HTTP.SET_PROXY('<proxy-hostname>:<proxy-port>');
```

e. Grant connect privilege for a host using the `DBMS_NETWORK_ACL_ADMIN` procedure. This example uses `*` to allow any host. However, you can explicitly specify each host that you want to connect to.

```
BEGIN
  DBMS_NETWORK_ACL_ADMIN.APPEND_HOST_ACE(
    host => '*',
    ace => xs$ace_type(privilege_list => xs$name_list('connect'),
                       principal_name => 'docuser',
                       principal_type => xs_acl.ptype_db));
END;
/
```

2. Set up your credentials for the REST provider that you want to access and then call `UTL_TO_SUMMARY`:

- **Using Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI**:

   a. Run `DBMS_VECTOR_CHAIN.CREATE_CREDENTIAL` to create and store a credential.

   Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI require the following authentication parameter:

   `{ "access_token": "<access token>" }`

   You will later refer to this credential name when declaring JSON parameters for the `UTL_TO_SUMMARY` call.

```
exec dbms_vector_chain.drop_credential('<credential name>');


declare
  jo json_object_t;
begin
  jo := json_object_t();
  jo.put('access_token', '<access token>');
  dbms_vector_chain.create_credential(
    credential_name   => '<credential name>',
    params            => json(jo.to_string));
end;
/
```

   Replace the `access_token` and `credential_name` values. For example:

```
declare
  jo json_object_t;
begin
  jo := json_object_t();
  jo.put('access_token', 'AbabA1B123aBc123AbabAb123a1a2ab');
  dbms_vector_chain.create_credential(
    credential_name   => 'HF_CRED',
    params            => json(jo.to_string));
end;
/
```

b. Run `DBMS_VECTOR_CHAIN.UTL_TO_SUMMARY`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for text summarization service>",
  "model": "<REST provider text summarization model name>"
}';

select dbms_vector_chain.utl_to_summary(
  'A transaction is a logical, atomic unit of work that contains
one or more SQL
    statements.
    An RDBMS must be able to group SQL statements so that they are
either all
    committed, which means they are applied to the database, or
all rolled back, which
    means they are undone.
    An illustration of the need for transactions is a funds
transfer from a savings account to
    a checking account. The transfer consists of the following
separate operations:
    1. Decrease the savings account.
    2. Increase the checking account.
    3. Record the transaction in the transaction journal.
    Oracle Database guarantees that all three operations succeed
or fail as a unit. For
    example, if a hardware failure prevents a statement in the
transaction from executing,
    then the other statements must be rolled back.
    Transactions set Oracle Database apart from a file system. If
you
    perform an atomic operation that updates several files, and if
the system fails halfway
    through, then the files will not be consistent. In contrast, a
transaction moves an
    Oracle database from one consistent state to another. The
basic principle of a
    transaction is "all or nothing": an atomic operation succeeds
or fails as a whole.',
  json(:params)) from dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  output clob;
begin
  input := 'A transaction is a logical, atomic unit of work
that contains one or more SQL
    statements.
    An RDBMS must be able to group SQL statements so that
they are either all
    committed, which means they are applied to the database,
or all rolled back, which
    means they are undone.
    An illustration of the need for transactions is a funds
transfer from a savings account to
    a checking account. The transfer consists of the
following separate operations:
    1. Decrease the savings account.
    2. Increase the checking account.
    3. Record the transaction in the transaction journal.
    Oracle Database guarantees that all three operations
succeed or fail as a unit. For
    example, if a hardware failure prevents a statement in
the transaction from executing,
    then the other statements must be rolled back.
    Transactions set Oracle Database apart from a file
system. If you
    perform an atomic operation that updates several files,
and if the system fails halfway
    through, then the files will not be consistent. In
contrast, a transaction moves an
    Oracle database from one consistent state to another.
The basic principle of a
    transaction is "all or nothing": an atomic operation
succeeds or fails as a whole.';

  params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for text summarization
service>",
  "model": "<REST provider text summarization model name>"
}';

  output := dbms_vector_chain.utl_to_summary(input,
json(params));
  dbms_output.put_line(output);
  if output is not null then
    dbms_lob.freetemporary(output);
  end if;
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `provider`, `credential_name`, `url`, and `model` values. Optionally, you can specify additional REST provider parameters.

Cohere example:

```
{
  "provider": "cohere",
  "credential_name": "COHERE_CRED",
  "url": "https://api.cohere.example.com/summarize",
  "model": "summarize-model",
  "length": "medium",
  "format": "paragraph",
  "temperature": 1.0
}
```

Google AI example:

```
{
  "provider": "googleai",
  "credential_name": "GOOGLEAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "summarize-model",
  "generation_config": {
    "temperature": 0.9,
    "topP": 1,
    "candidateCount": 1,
    "maxOutputTokens": 256
  }
}
```

Hugging Face example:

```
{
  "provider": "huggingface",
  "credential_name": "HF_CRED",
  "url": "https://api.huggingface.example.co/models/",
  "model": "summarize-model",
  "wait_for_model": "true"
}
```

OpenAI example:

```
{
  "provider": "openai",
  "credential_name": "OPENAI_CRED",
  "url": "https://api.openai.example.com",
  "model": "summarize-model",
  "max_tokens": 256,
  "temperature": 1.0
}
```

Vertex AI example:

```
{
  "provider": "vertexai",
  "credential_name": "VERTEXAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "summarize-model",
  "generation_config": {
    "temperature": 0.9,
    "topP": 1,
    "candidateCount": 1,
    "maxOutputTokens": 256
  }
}
```

- **Using Generative AI**:

  a. Run `DBMS_VECTOR_CHAIN.CREATE_CREDENTIAL` to create and store an OCI credential (`OCI_CRED`).

     Generative AI requires the following authentication parameters:

```
{
"user_ocid": "<user ocid>",
"tenancy_ocid": "<tenancy ocid>",
"compartment_ocid": "<compartment ocid>",
"private_key": "<private key>",
"fingerprint": "<fingerprint>"
}
```

You will later refer to this credential name when declaring JSON parameters for the `UTL_TO_SUMMARY` call.

> **Note:**
>
> The generated private key may appear as:
>
> ```
> -----BEGIN RSA PRIVATE KEY-----
> <private key string>
> -----END RSA PRIVATE KEY-----
> ```
>
> You pass the *`<private key string>`* value (excluding the `BEGIN` and `END` lines), either as a single line or as multiple lines.

```
exec dbms_vector_chain.drop_credential('OCI_CRED');


declare
  jo json_object_t;
begin
  jo := json_object_t();
```

```
  jo.put('user_ocid','<user ocid>');
  jo.put('tenancy_ocid','<tenancy ocid>');
  jo.put('compartment_ocid','<compartment ocid>');
  jo.put('private_key','<private key>');
  jo.put('fingerprint','<fingerprint>');
  dbms_output.put_line(jo.to_string);
  dbms_vector_chain.create_credential(
    credential_name   => 'OCI_CRED',
    params            => json(jo.to_string));
end;
/
```

Replace all the authentication parameter values.

For example:

```
declare
  jo json_object_t;
begin
  jo := json_object_t();

jo.put('user_ocid','ocid1.user.oc1..aabbalbbaa1112233aabbaabb111122
2aa1111bb');

jo.put('tenancy_ocid','ocid1.tenancy.oc1..aaaaalbbbb1112233aaaabbaa
1111222aaa111a');

jo.put('compartment_ocid','ocid1.compartment.oc1..ababalabab1112233
abababab1111222aba11ab');

jo.put('private_key','AAAaaaBBB11112222333...AAA111AAABBB222aaa1a/
+');

jo.put('fingerprint','01:1a:a1:aa:12:a1:12:1a:ab:12:01:ab:a1:12:ab:
1a');
  dbms_output.put_line(jo.to_string);
  dbms_vector_chain.create_credential(
    credential_name   => 'OCI_CRED',
    params            => json(jo.to_string));
end;
/
```

b. Run `DBMS_VECTOR_CHAIN.UTL_TO_SUMMARY`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for text summarization service>",
  "model": "<REST provider text summarization model name>"
}';
```

```
select dbms_vector_chain.utl_to_summary(
  'A transaction is a logical, atomic unit of work that
contains one or more SQL
    statements.
    An RDBMS must be able to group SQL statements so that
they are either all
    committed, which means they are applied to the database,
or all rolled back, which
    means they are undone.
    An illustration of the need for transactions is a funds
transfer from a savings account to
    a checking account. The transfer consists of the
following separate operations:
    1. Decrease the savings account.
    2. Increase the checking account.
    3. Record the transaction in the transaction journal.
    Oracle Database guarantees that all three operations
succeed or fail as a unit. For
    example, if a hardware failure prevents a statement in
the transaction from executing,
    then the other statements must be rolled back.
    Transactions set Oracle Database apart from a file
system. If you
    perform an atomic operation that updates several files,
and if the system fails halfway
    through, then the files will not be consistent. In
contrast, a transaction moves an
    Oracle database from one consistent state to another.
The basic principle of a
    transaction is all or nothing: an atomic operation
succeeds or fails as a whole.',
  json(:params)) from dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  output clob;
begin
  input := 'A transaction is a logical, atomic unit of work
that contains one or more SQL
    statements.
    An RDBMS must be able to group SQL statements so that
they are either all
    committed, which means they are applied to the database,
or all rolled back, which
    means they are undone.
    An illustration of the need for transactions is a funds
transfer from a savings account to
    a checking account. The transfer consists of the
following separate operations:
    1. Decrease the savings account.
    2. Increase the checking account.
    3. Record the transaction in the transaction journal.
    Oracle Database guarantees that all three operations succeed
or fail as a unit. For
    example, if a hardware failure prevents a statement in the
transaction from executing,
    then the other statements must be rolled back.
    Transactions set Oracle Database apart from a file system. If
you
    perform an atomic operation that updates several files, and if
the system fails halfway
    through, then the files will not be consistent. In contrast, a
transaction moves an
    Oracle database from one consistent state to another. The
basic principle of a
    transaction is all or nothing: an atomic operation succeeds or
fails as a whole.';

  params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for text summarization service>",
  "model": "<REST provider text summarization model name>"
}';

  output := dbms_vector_chain.utl_to_summary(input, json(params));
  dbms_output.put_line(output);
  if output is not null then
    dbms_lob.freetemporary(output);
  end if;
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `url` and `model` values. Optionally, you can specify additional REST provider-specific parameters.

For example:

```
{
 "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "https://generativeai.oci.example.com/summarizeText",
  "model": "summarize.modelname",
  "length": "MEDIUM",
  "format": "PARAGRAPH",
  "temperature": 1.0
}
```

The generated summary appears as follows:

```
A transaction is a logical unit of work that groups one or more SQL
statements
```

```
that must be executed as a unit, with all statements succeeding, or
all
statements being rolled back. Transactions are a fundamental
concept in
relational database management systems (RDBMS), and Oracle Database
is
specifically designed to manage transactions, ensuring database
consistency and
integrity. Transactions differ from file systems in that they
maintain
atomicity, ensuring that all related operations succeed or fail as
a whole,
maintaining database consistency regardless of intermittent
failures.
Transactions move a database from one consistent state to another,
and the
fundamental principle is that a transaction is committed or rolled
back as a
whole, upholding the "all or nothing" principle.

PL/SQL procedure successfully completed.
```

This example uses the default settings for each provider. For detailed information on additional parameters, refer to your third-party provider's documentation.

Related Topics

- UTL_TO_SUMMARY

Create and Use Custom Vocabulary

You can see how to create and use your own vocabulary of tokens when chunking data.

Here, you use the chunker helper function `CREATE_VOCABULARY` from the `DBMS_VECTOR_CHAIN` package to load custom vocabulary. This vocabulary file contains a list of tokens, recognized by your model's tokenizer.

1. Start SQL*Plus and connect to Oracle Database as a local test user:
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba


      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

b. Create a local test user (`docuser`) and grant necessary privileges:

```
drop user docuser cascade;


create user docuser identified by docuser DEFAULT TABLESPACE tbs1
quota unlimited on tbs1;


grant DB_DEVELOPER_ROLE to docuser;
```

c. Create a local directory on your server (`VEC_DUMP`) to store your vocabulary file. Grant necessary privileges:

```
create or replace directory VEC_DUMP as '/my_local_dir/';


grant read, write on directory VEC_DUMP to docuser;

commit;
```

d. Transfer the vocabulary file for your required model to the `VEC_DUMP` directory.

   For example, if using WordPiece tokenization, you can download and transfer the `vocab.txt` vocabulary file for "bert-base-uncased".

e. Connect to Oracle Database as the test user and alter the environment settings for your session:

```
conn docuser/password@CDB_PDB;

SET ECHO ON
SET FEEDBACK 1
SET NUMWIDTH 10
SET LINESIZE 80
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

2. Create a relational table (`doc_vocabtab`) to store your vocabulary tokens in it:

```
CREATE TABLE doc_vocabtab(token nvarchar2(64))
  ORGANIZATION EXTERNAL
  (default directory VEC_DUMP
   ACCESS PARAMETERS (RECORDS DELIMITED BY NEWLINE)
   location ('bert-vocabulary-uncased.txt'));
```

3. Run `DBMS_VECTOR_CHAIN.CREATE_VOCABULARY` to create a vocabulary (`doc_vocab`).

```
DECLARE
  vocab_params clob := '{"table_name"      : "doc_vocabtab",
                       "column_name"      : "token",
                       "vocabulary_name"  : "doc_vocab",
                       "format"           : "bert",
                      "cased"            : false}';

BEGIN
  dbms_vector_chain.create_vocabulary(json(vocab_params));
END;
/
```

After loading the token vocabulary, you can now use the `BY VOCABULARY` chunking mode (with `VECTOR_CHUNKS` or `UTL_TO_CHUNKS`) to split data by counting the number of tokens.

Related Topics

- CREATE_VOCABULARY
- VECTOR_CHUNKS
- UTL_TO_CHUNKS

Create and Use Custom Language Data

You can create and use your own language-specific conditions (such as common abbreviations) when chunking data.

Here, you use the chunker helper function `CREATE_LANG_DATA` from the `DBMS_VECTOR_CHAIN` package to load the data file for Simplified Chinese. This data file contains abbreviation tokens for your chosen language.

1. Start SQL*Plus and connect to Oracle Database as a local test user:
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba


      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

   b. Create a local test user (`docuser`) and grant necessary privileges:

      ```
      drop user docuser cascade;


      create user docuser identified by docuser DEFAULT TABLESPACE
      tbs1 quota unlimited on tbs1;


      grant DB_DEVELOPER_ROLE to docuser;
      ```

c. Create a local directory on your server (`VEC_DUMP`) to store your language data file. Grant necessary privileges:

```
create or replace directory VEC_DUMP as '/my_local_dir/';


grant read, write on directory VEC_DUMP to docuser;

commit;
```

d. Transfer the data file for your required language to the `VEC_DUMP` directory. For example, `dreoszhs.txt` for Simplified Chinese.

   To know the data file location for your language, see Supported Languages and Data File Locations.

e. Connect to Oracle Database as the test user and alter the environment settings for your session:

```
conn docuser/password@CDB_PDB;

SET ECHO ON
SET FEEDBACK 1
SET NUMWIDTH 10
SET LINESIZE 80
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

2. Create a relational table (`doc_langtab`) to store your abbreviation tokens in it:

```
CREATE TABLE doc_langtab(token nvarchar2(64))
  ORGANIZATION EXTERNAL
  (default directory VEC_DUMP
   ACCESS PARAMETERS (RECORDS DELIMITED BY NEWLINE CHARACTERSET AL32UTF8)
   location ('dreoszhs.txt'));
```

3. Run `DBMS_VECTOR_CHAIN.CREATE_LANG_DATA` to create language data (`doc_lang_data`).

```
DECLARE
  lang_params clob := '{"table_name"      : "doc_langtab",
                        "column_name"     : "token",
                        "language"        : "simplified chinese",
                        "preference_name" : "doc_lang_data"}';
BEGIN
  dbms_vector_chain.create_lang_data(json(lang_params));
END;
/
```

After loading the language data, you can now use language-specific chunking by specifying the `LANGUAGE` chunking parameter with `VECTOR_CHUNKS` or `UTL_TO_CHUNKS`.

Related Topics

- CREATE_LANG_DATA

- VECTOR_CHUNKS
- UTL_TO_CHUNKS

Perform Chunking: SQL and PL/SQL Examples

In these examples, you can see how to extract chunks from text strings and PDF documents.

- Convert Text to Chunks With Custom Chunking Specifications
  A chunked output, especially for long and complex documents, sometimes loses contextual meaning or coherence with its parent content. In this example, you can see how to refine your chunks by applying custom chunking specifications.
- Explore Chunking Techniques and Examples
  Review these examples of all the supported chunking parameters. These examples can provide an idea on what are good and bad chunking techniques, and thus help you define a strategy while chunking your data.

Convert Text to Chunks With Custom Chunking Specifications

A chunked output, especially for long and complex documents, sometimes loses contextual meaning or coherence with its parent content. In this example, you can see how to refine your chunks by applying custom chunking specifications.

Here, you use the `VECTOR_CHUNKS` SQL function or the `UTL_TO_CHUNKS()` PL/SQL function from the `DBMS_VECTOR_CHAIN` package.

1. Start SQL*Plus and connect to Oracle Database as a local test user.
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba
      ```

      ```
      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

   b. Create a local test user (`docuser`) and grant necessary privileges:

      ```
      DROP USER docuser cascade;
      ```

      ```
      CREATE USER docuser identified by docuser DEFAULT TABLESPACE
      tbs1 quota unlimited on tbs1;
      ```

      ```
      GRANT DB_DEVELOPER_ROLE to docuser;
      ```

c. Connect to Oracle Database as the test user and alter the environment settings for your session:

```
CONN docuser/password@CDB_PDB


SET ECHO ON
SET FEEDBACK 1
SET NUMWIDTH 10
SET LINESIZE 80
SET TRIMSPOOL ON
SET TAB OFF
SET PAGESIZE 10000
SET LONG 10000
```

2. Create a relational table (`documentation_tab`) to store unstructured text chunks in it:

```
DROP TABLE IF EXISTS documentation_tab;

CREATE TABLE documentation_tab (
    id NUMBER,
    text VARCHAR2(2000));


INSERT INTO documentation_tab VALUES(1,
'Oracle AI Vector Search stores and indexes vector embeddings'||
' for fast retrieval and similarity search.'||CHR(10)||CHR(10)||
'     About Oracle AI Vector Search'||CHR(10)||
'     Vector Indexes are a new classification of specialized indexes'||
' that are designed for Artificial Intelligence (AI) workloads that
allow'||
' you to query data based on semantics, rather than keywords.'||CHR(10)||
CHR(10)||
'     Why Use Oracle AI Vector Search?'||CHR(10)||
' The biggest benefit of Oracle AI Vector Search is that semantic
search'||
' on unstructured data can be combined with relational search on
business'||
' data in one single system.'||CHR(10));

COMMIT;


SET LINESIZE 1000;
SET PAGESIZE 200;
COLUMN doc FORMAT 999;
COLUMN id  FORMAT 999;
COLUMN pos FORMAT 999;
COLUMN siz FORMAT 999;
COLUMN txt FORMAT a60;
COLUMN data FORMAT a80;
```

3. Call the `VECTOR_CHUNKS` SQL function and specify the following custom chunking parameters:

```
SELECT D.id doc, C.chunk_offset pos, C.chunk_length siz,
C.chunk_text txt
FROM documentation_tab D, VECTOR_CHUNKS(D.text
    BY words
    MAX 50
    OVERLAP 0
    SPLIT BY recursively
    LANGUAGE american
    NORMALIZE all) C;
```

To call the same operation using the `UTL_TO_CHUNKS` function from the `DBMS_VECTOR_CHAIN` package, run:

```
SELECT D.id doc,
    JSON_VALUE(C.column_value, '$.chunk_id' RETURNING NUMBER) AS id,
    JSON_VALUE(C.column_value, '$.chunk_offset' RETURNING NUMBER)
AS pos,
    JSON_VALUE(C.column_value, '$.chunk_length' RETURNING NUMBER)
AS siz,
    JSON_VALUE(C.column_value, '$.chunk_data') AS txt
FROM documentation_tab D,
   dbms_vector_chain.utl_to_chunks(D.text,
   JSON('{"by":"words",
          "max":"50",
          "overlap":"0",
          "split":"recursively",
          "language":"american",
          "normalize":"all"}')) C;
```

This returns a set of three chunks, which are split by words recursively using blank lines, new lines, and spaces:

```
DOC  POS  SIZ  TXT
---- ---- ----
------------------------------------------------------------
1    1    108  Oracle AI Vector Search stores and indexes vector
embeddings
         for fast retrieval and similarity search.

1    109  234  About Oracle AI Vector Search
            Vector Indexes are a new classification of specialized
index
            es that are designed for Artificial Intelligence (AI)
worklo
            ads that allow you to query data based on semantics,
rather
            than keywords.

1    343  204  Why Use Oracle AI Vector Search?
            The biggest benefit of Oracle AI Vector Search is that
```

```
seman
            tic search on unstructured data can be combined with relatio
            nal search on business data in one single system.
```

4. To further clean up the chunking results, supply JSON parameters for `UTL_TO_CHUNKS`:

```
SELECT C.*
FROM documentation_tab D,
   dbms_vector_chain.utl_to_chunks(D.text,
   JSON('{"by":"words",
          "max":"50",
          "overlap":"0",
          "split":"recursively",
          "language":"american",
          "normalize":"all"}')) C;
```

This returns chunk texts in JSON format:

```
COLUMN_VALUE
--------------------------------------------------------------------------
------
{"chunk_id":1,"chunk_offset":1,"chunk_length":108,"chunk_data":"Oracle AI
Vector
 Search stores and indexes vector embeddings for fast retrieval and
similarity s
earch."}

{"chunk_id":2,"chunk_offset":109,"chunk_length":234,"chunk_data":"About
Oracle A
I Vector Search\nVector Indexes are a new classification of specialized
indexes
that are designed for Artificial Intelligence (AI) workloads that allow
you to q
uery data based on semantics, rather than keywords."}

{"chunk_id":3,"chunk_offset":343,"chunk_length":204,"chunk_data":"Why Use
Oracle
 AI Vector Search?\nThe biggest benefit of Oracle AI Vector Search is
that seman
tic search on unstructured data can be combined with relational search on
busine
ss data in one single system."}
```

The chunking results contain:

- `chunk_id`: Chunk ID for each chunk
- `chunk_offset`: Original position of each chunk in the source document, relative to the start of document (which has a position of `1`)
- `chunk_length`: Character length of each chunk
- `chunk_data`: Text pieces from each chunk

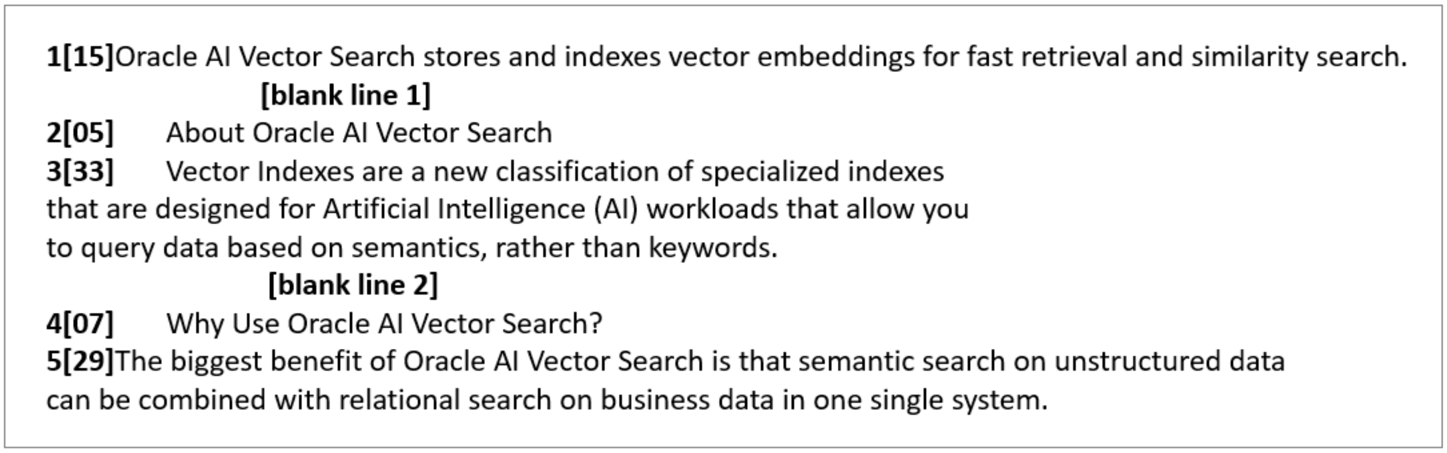
Related Topics

- VECTOR_CHUNKS
- UTL_TO_CHUNKS

Explore Chunking Techniques and Examples

Review these examples of all the supported chunking parameters. These examples can provide an idea on what are good and bad chunking techniques, and thus help you define a strategy while chunking your data.

Here, you can see how the following sample text of five lines is split when you apply various chunking parameters to it:



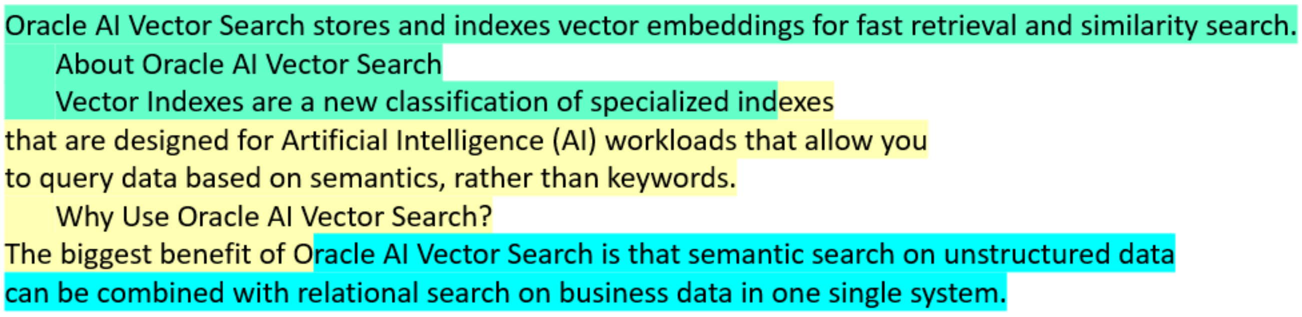
1[15]Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
[blank line 1]
2[05] About Oracle AI Vector Search
3[33] Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
[blank line 2]
4[07] Why Use Oracle AI Vector Search?
5[29]The biggest benefit of Oracle AI Vector Search is that semantic search on unstructured data
can be combined with relational search on business data in one single system.

- The lines are numbered as a reference for the explanations and include the word count in square brackets (for example, `1[15]`). The blank lines are also noted.
- The start and end boundaries of chunks are represented with colored markers.
- To perform examples with the `BY VOCABULARY` mode, you must create custom vocabulary beforehand (for example, `DOC_VOCAB`). See Create and Use Custom Vocabulary.

Example 3-1 BY chars MAX 200 OVERLAP 0 SPLIT BY none

This example shows the simplest form of chunking, where you split the text by a fixed number of characters (including the end-of-line characters), at whatever point that occurs in the text.

The text from the first chunk is split at an absolute maximum character of `200`, which divides the word `indexes` between the first two chunks. Similarly, you can see the word `Oracle` splitting between second and third chunks.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search on unstructured data
can be combined with relational search on business data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY chars MAX 200 OVERLAP 0
                           SPLIT BY none LANGUAGE american NORMALIZE none) C;
```

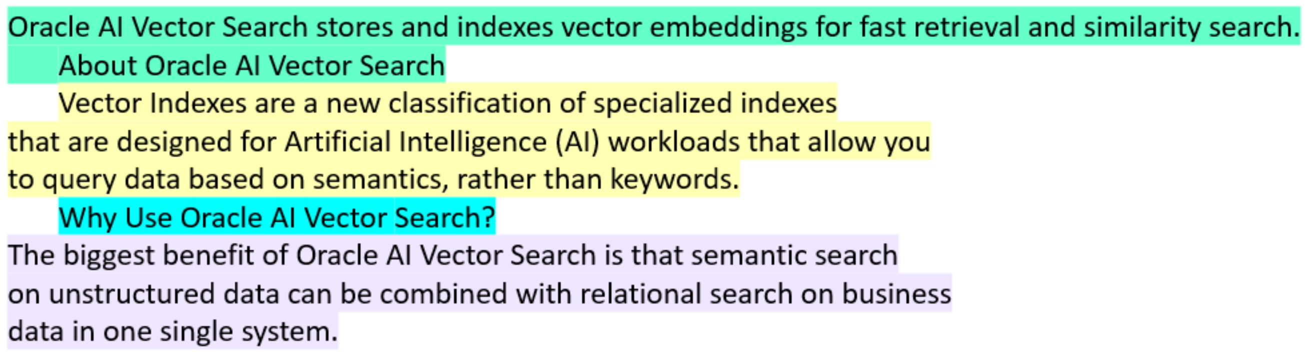
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-------------------------------------------------------------------------
1         200          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized ind

201         200          exes that are designed for Artificial Intelligence
(AI) workloads that allow you to query data based on semantics, rather than
keywords.

                          Why Use Oracle AI Vector Search?
                          The biggest benefit of O

401         146          racle AI Vector Search is that semantic search on
unstructured data can be combined with relational search on business data in
one single system.
```

Example 3-2 BY chars MAX 200 OVERLAP 0 SPLIT BY newline

In this example, the text is split into four chunks at new lines, if possible, within the maximum limit of `200` characters.

The text from the first chunk is split after the second line because the third line would exceed the maximum. The third line fits within the maximum perfectly. The fourth and fifth line would also exceed the maximum, so it produces two chunks.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY chars MAX 200
OVERLAP 0
                           SPLIT BY newline LANGUAGE american
NORMALIZE none) C;
```

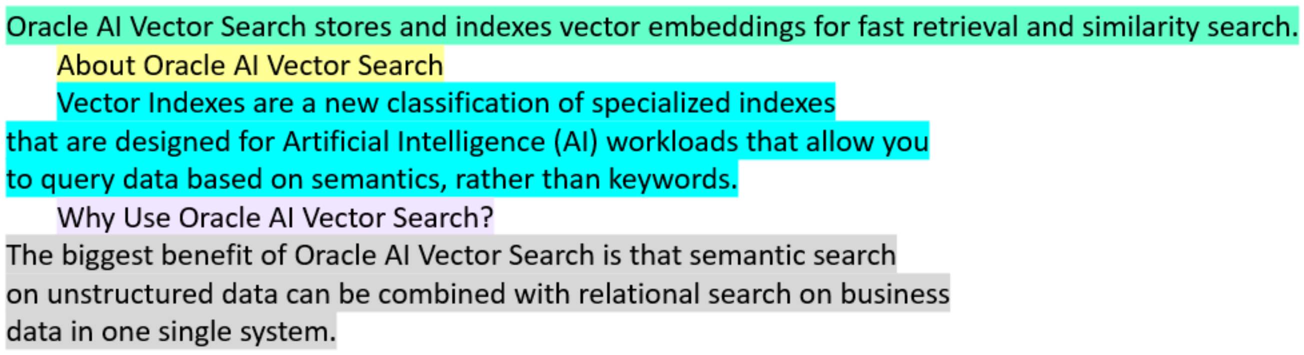
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1          138         Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search

143          196          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads that allow you to query data based on semantics, rather than
keywords.

343          33           Why Use Oracle AI Vector Search?

377          170          The biggest benefit of Oracle AI Vector
Search is that semantic search on unstructured data can be combined
with relational search on business data in one single system.
```

Example 3-3 BY chars MAX 200 OVERLAP 0 SPLIT BY recursively

In this example, the text is split into five chunks recursively using blank lines, newlines and then spaces, if possible, within the maximum of `200` characters.

The first chunk is split after the first blank line because including the text after the second blank line would exceed the maximum. The second passage exceeds the maximum on its own, so it is broken into two chunks at the new lines. Similarly, the third section is also broken into two chunks at the new lines.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

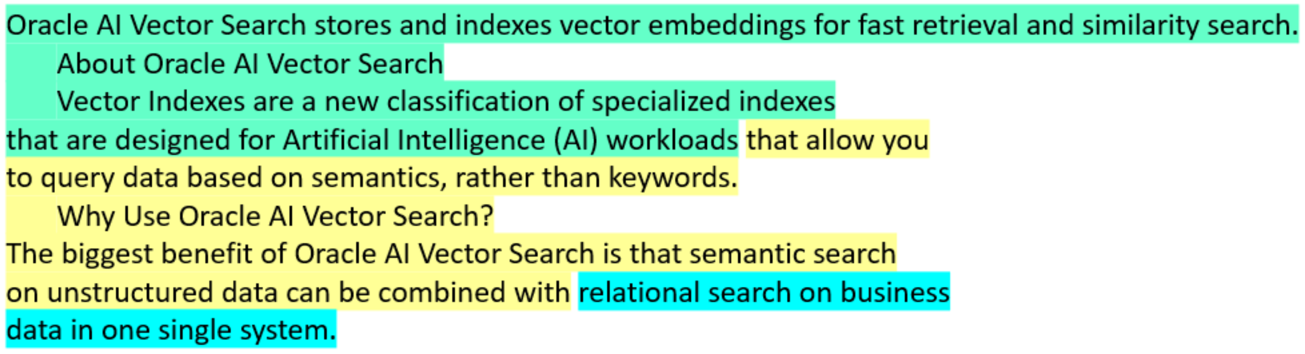
```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY chars MAX 200 OVERLAP 0
                           SPLIT BY recursively LANGUAGE american NORMALIZE
none) C;
```

Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
---------------------
1            104          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

109         30           About Oracle AI Vector Search

143         196          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads that allow you to query data based on semantics, rather than
keywords.

343         33           Why Use Oracle AI Vector Search?

377         170          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be combined with relational
search on business data in one single system.
```

Example 3-4   BY words MAX 40 OVERLAP 0 SPLIT BY none

In this example, the text is split into three chunks at an absolute maximum word of `40`, the third line after `wordloads` and the fifth line after `with`.


Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP
0
                           SPLIT BY none LANGUAGE american NORMALIZE
none) C;
```

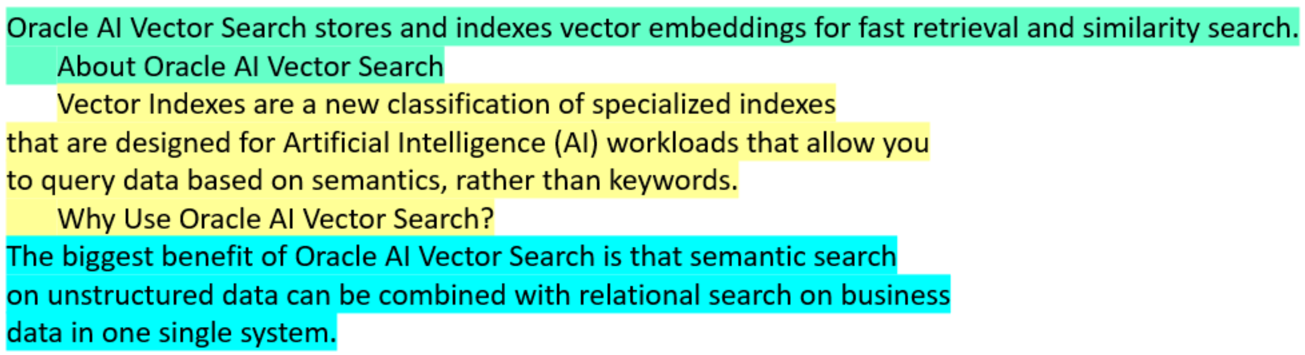
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1          266          Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial
                          Intelligence (AI) workloads

267          223          that allow you to query data based on
semantics, rather than keywords.

                          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vector
Search is that semantic search on unstructured data can be combined
with


490          57           relational search on business data in one
single system.
```

Example 3-5   BY words MAX 40 OVERLAP 0 SPLIT BY newline

In this example, the text is split into chunks at new lines, if possible, within the maximum of `40` words.

The first chunk (of 21 words) is split after the second line, as the third line would exceed the maximum number of words (21+33 words). The third and fourth lines fit within the maximum. The fifth line is 29 words, so fits in the last chunk.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
    About Oracle AI Vector Search
    Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
    Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP 0
                           SPLIT BY newline LANGUAGE american NORMALIZE
none) C;
```

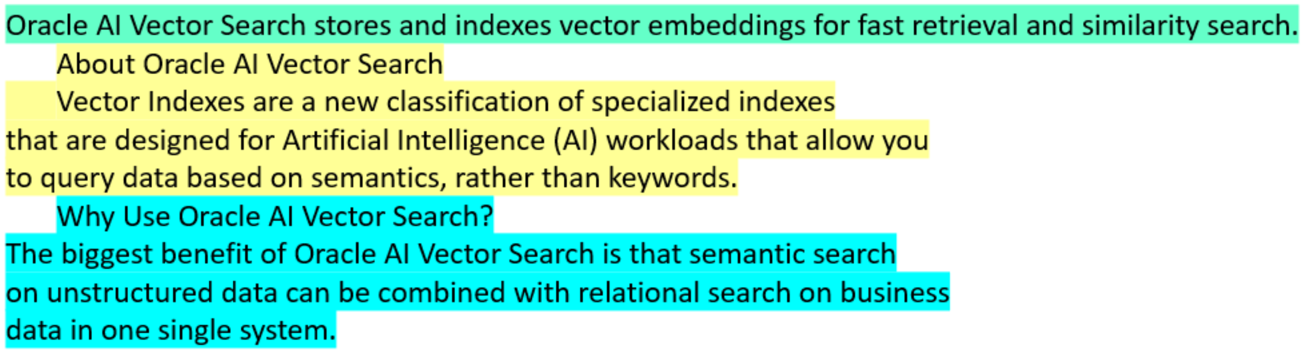
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
---------------------
1         138          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search

143         233          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads that allow you to query data based on semantics, rather than
keywords.

                          Why Use Oracle AI Vector Search?

377          170          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be combined with relational
search on business data in one single system.
```

Example 3-6   BY words MAX 40 OVERLAP 0 SPLIT BY recursively

In this example, the chunks are split by words recursively using blank lines, newlines, and spaces.

The text after the second blank line exceeds the maximum words, so the first chunk ends at the first blank line. The second chunk (of 38 words) ends at the next blank line. The final chunk (of 35 words) consists of the rest of the input.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

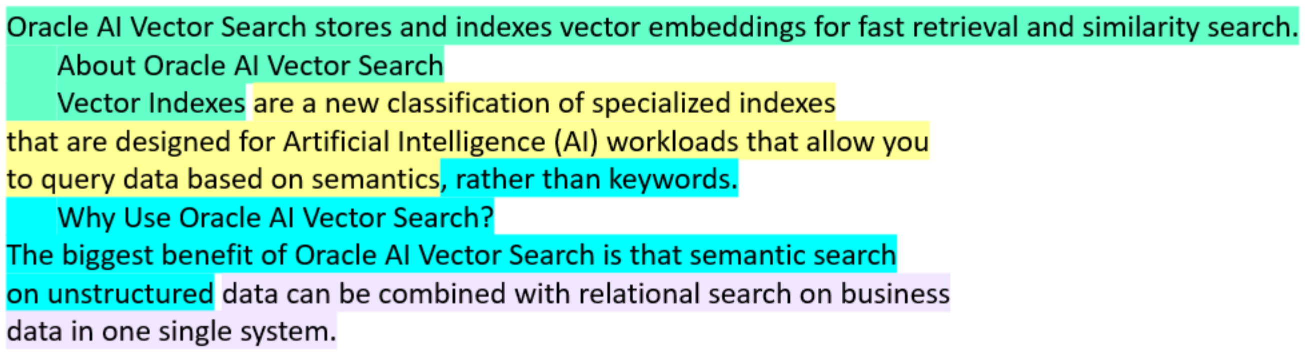
```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP
0
                           SPLIT BY recursively LANGUAGE american
NORMALIZE none) C;
```

Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1          104          Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

109         230          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial
                          Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.

343         204          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vector
Search is that semantic search on unstructured data can be
                          combined with relational search on business
data in one single system.
```

Example 3-7 BY vocabulary MAX 40 OVERLAP 0 SPLIT BY none

In this example, the text is split into four chunks at an absolute maximum vocabulary token of 40, which contrasts with the three chunks produced in the Example 3-4 example. This is because vocabulary tokens include pieces of words, so the chunk text is generally smaller than simple word splitting.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
    About Oracle AI Vector Search
    Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
    Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY vocabulary doc_vocab MAX
40 OVERLAP 0
                           SPLIT BY none LANGUAGE american NORMALIZE none) C;
```

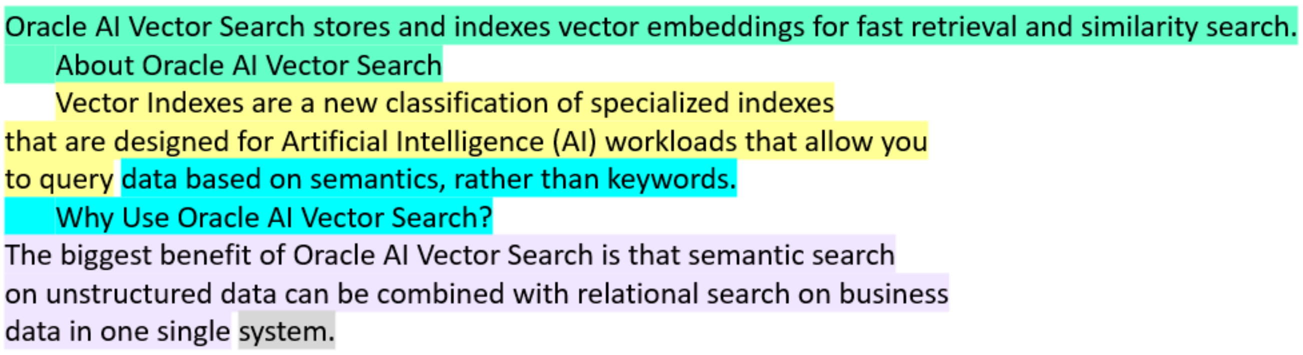
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
------------------------------------------------------------------------------
---------------------
1         157         Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search
                          Vector Indexes
158         156         are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics

314          150          , rather than keywords.

                          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured

464         83           data can be combined with relational search on
business data in one single system.
```

Example 3-8   BY vocabulary MAX 40 OVERLAP 0 SPLIT BY newline

In this example, the text is split into five chunks with newlines, using an absolute maximum vocabulary token of 40, which contrasts with the Example 3-5 example.

Vocabulary tokens include pieces of words, so the chunk text is generally smaller than simple word splitting. This example produces five chunks rather than 3 in example A-5, with the middle passage split into two, and the final word unable to fit into the 4th chunk.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY vocabulary doc_vocab
MAX 40 OVERLAP 0
                           SPLIT BY newline LANGUAGE american
NORMALIZE none) C;
```

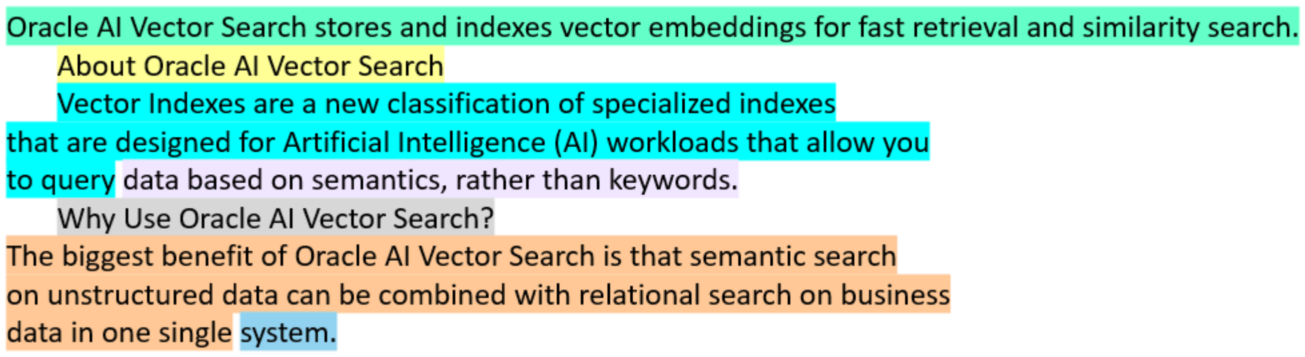
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1         138          Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search

143         148          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads that allow you to query

291         85           data based on semantics, rather than keywords.

                          Why Use Oracle AI Vector Search?

377         162          The biggest benefit of Oracle AI Vector
Search is that semantic search on unstructured data can be combined
with relational search on business data in one single

539         8            system.
```

Example 3-9   BY vocabulary MAX 40 OVERLAP 0 SPLIT BY recursively

In this example, the text is split into seven chunks recursively using blank lines, new lines, and spaces and an absolute maximum vocabulary token of 40, which contrasts with the three chunks produced in the Example 3-6 example.

Vocabulary tokens include pieces of words, so the chunk text is generally smaller than simple word splitting. This example produces seven chunks with the middle passage split into three and the final passage split into three.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY vocabulary doc_vocab MAX
40 OVERLAP 0
                           SPLIT BY recursively LANGUAGE american NORMALIZE
none) C;
```

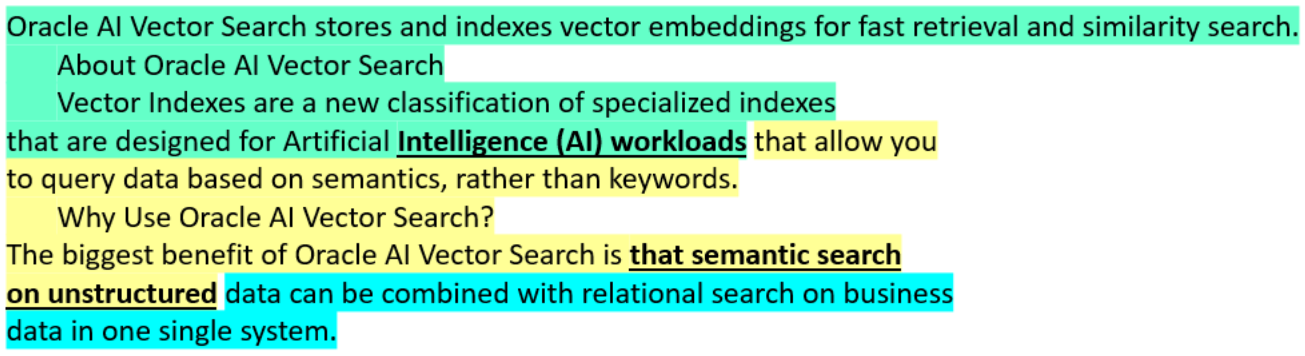
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
---------------------
1         104          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

109         30           About Oracle AI Vector Search

143         148          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads that allow you to query

291         48           data based on semantics, rather than keywords.

343         33           Why Use Oracle AI Vector Search?

377         162          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be combined with relational
search on business data in one single

539         8            system.
```

Example 3-10 BY words MAX 40 OVERLAP 5 SPLIT BY none

This example is the similar to Example 3-4, except an overlap of `5` is used.

The first chunk ends at the maximum 40 words (after `workloads`). The second chunk overlaps with the last 5 words including parentheses of the first chunk, and ends after `unstructured`. The overlapping words are underlined below. The third chunk overlaps with the last 5 words, which are also underlined.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial **Intelligence (AI) workloads** that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is **that semantic search**
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP
5
                           SPLIT BY none LANGUAGE american NORMALIZE
none) C;
```

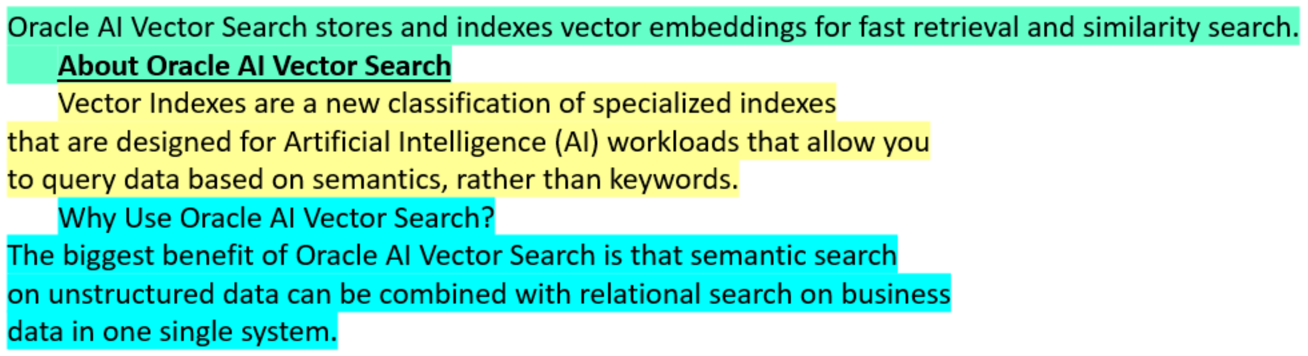
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
--------------------------
1         266        Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

                         About Oracle AI Vector Search
                         Vector Indexes are a new classification of
specialized indexes that are designed for Artificial Intelligence (AI)
workloads

239         225         Intelligence (AI) workloads that allow you to
query data based on semantics, rather than keywords.

                         Why Use Oracle AI Vector Search?
                         The biggest benefit of Oracle AI Vector
Search is that semantic search on unstructured

427         120         that semantic search on unstructured data can
be combined with relational search on business data in one single
system.
```

Example 3-11 BY words MAX 40 OVERLAP 5 SPLIT BY newline

This example is the similar to Example 3-5, except an overlap of 5 is used. The overlapping portion of a chunk must obey the same split condition, in this case must begin on a new line.

The first chunk ends at the second line, as the third line would exceed the maximum 40 words. The second chunk starts with the second line of 5 words of the first chunk (underlined below) and ends at the third line. The third chunk has no overlap because the preceding line exceeds the maximum of 5.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
    About Oracle AI Vector Search
    Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
    Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP 5
                           SPLIT BY newline LANGUAGE american NORMALIZE
none) C;
```

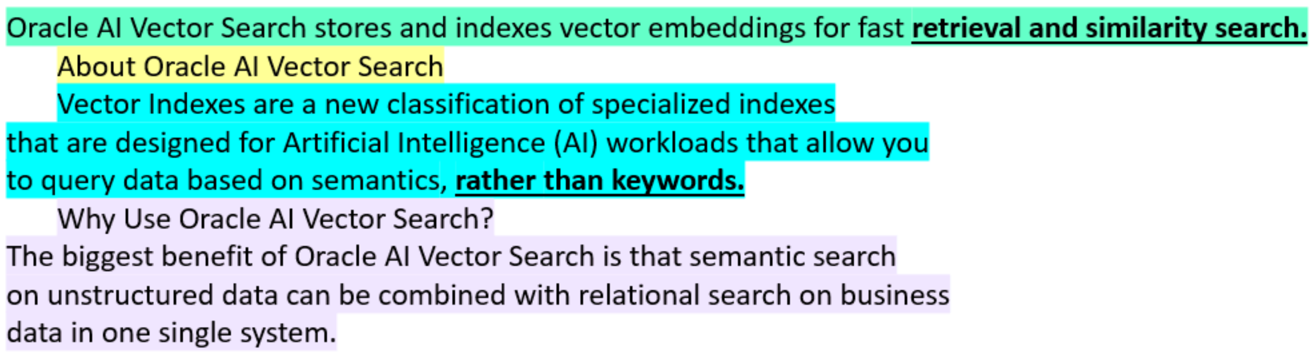
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
----------------------
1         138          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search

109         230          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial
                          Intelligence (AI) workloads that allow you to
query data based on semantics, rather than keywords.

343         204          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be
                          combined with relational search on business data
in one single system.
```

Example 3-12 BY words MAX 40 OVERLAP 5 SPLIT BY recursively

This example is the similar to Example 3-6, except an overlap of 5 is used. The overlapping portion of a chunk must obey the same split condition, in this case must begin at either a blank line, new line, or space.

The text after the second blank line exceeds the maximum words, so the first chunk ends at the first blank line. The second chunk overlaps with 5 words (beginning on a space; underlined below) and includes the second line, but excludes the third line of 33 words. The third chunk overlaps 5 words and ends on the second blank line. The fourth chunk consumes the rest of the input.



Oracle AI Vector Search stores and indexes vector embeddings for fast **retrieval and similarity search.**
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, **rather than keywords.**
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP
5
                           SPLIT BY recursively LANGUAGE american
NORMALIZE none) C;
```

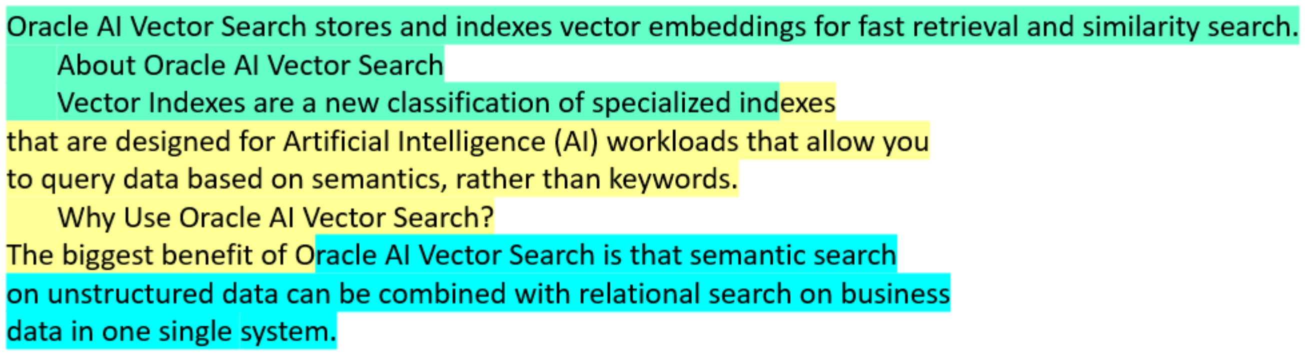
Output:

```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1         104         Oracle AI Vector Search stores and indexes
vector embeddings for fast retrieval and similarity search.

71           68          retrieval and similarity search.

                         About Oracle AI Vector Search

109          230         About Oracle AI Vector Search
                         Vector Indexes are a new classification of
specialized indexes that are designed for Artificial
                         Intelligence (AI) workloads that allow you to
query data based on semantics, rather than keywords.

316          231         rather than keywords.
```

```
                              Why Use Oracle AI Vector Search?
                              The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be
                              combined with relational search on business data in
one single system.
```

Example 3-13 BY chars MAX 200 OVERLAP 0 SPLIT BY none NORMALIZE none

This example is the same as Example 3-1, to contrast with Example 3-13 with normalization.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
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data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY chars MAX 200 OVERLAP 0
                                SPLIT BY none LANGUAGE american NORMALIZE none) C;
```

Output:

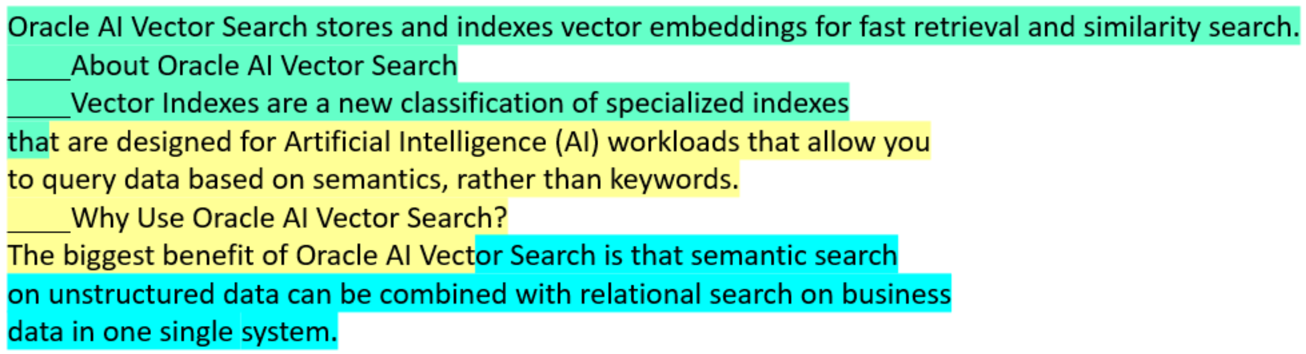
```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
---------------------
1          200          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized ind

201          200          exes that are designed for Artificial Intelligence
(AI) workloads that allow you to query data based
                          on semantics, rather than keywords.

                          Why Use Oracle AI Vector Search?
                          The biggest benefit of O

401          146          racle AI Vector Search is that semantic search on
unstructured data can be combined with relational
                          search on business data in one single system.
```

Example 3-14 BY chars MAX 200 OVERLAP 0 SPLIT BY none NORMALIZE whitespace

This example enables `whitespace` normalization, which collapses redundant white space to produce more content within a chunk maximum.

The first chunk extends 8 more characters due to the two indented lines of 4 spaces each (marked with underscores _ below). The second chunk extends 4 more characters due to the one indented line of 4 total spaces. The third chunk has the remaining input.

This example shows that the chunk length (normally in bytes) can differ from the chunk text's size. The `CHUNK_OFFSET` and `CHUNK_LENGTH` represent the original source location of the chunk.



Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
____About Oracle AI Vector Search
____Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
____Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY chars MAX 200 
OVERLAP 0
                           SPLIT BY none LANGUAGE american NORMALIZE 
whitespace) C;
```

Output:

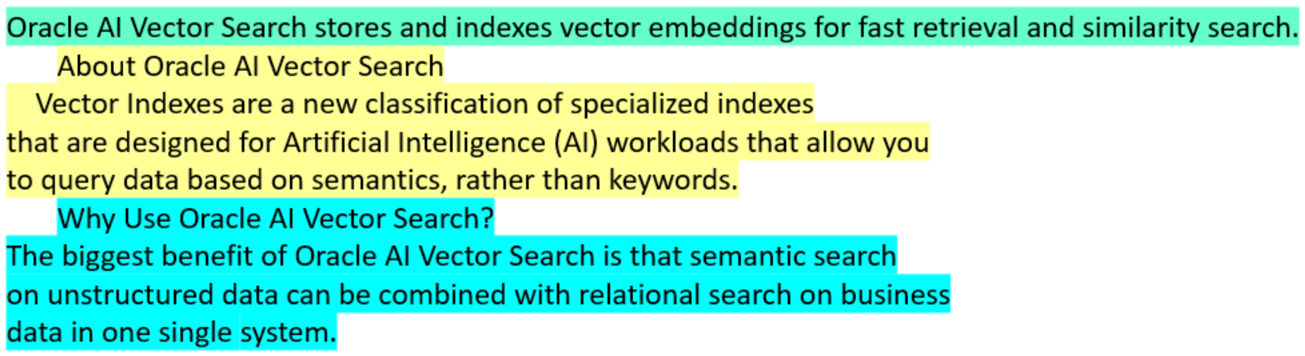
```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------
---------------------------
1          208          Oracle AI Vector Search stores and indexes 
vector embeddings for fast retrieval and similarity search.

                          About Oracle AI Vector Search
                          Vector Indexes are a new classification of 
specialized indexes tha

209          205          t are designed for Artificial Intelligence 
(AI) workloads that allow you to query data based on sema
                          ntics, rather than keywords.

                          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vect
```

```
414          133          or Search is that semantic search on unstructured
data can be combined with relational search on business data in one single
system.
```

Example 3-15 BY words MAX 40 OVERLAP 0 SPLIT BY sentence LANGUAGE American

This example uses end-of-sentence splitting which uses language-specific data and heuristics (such as sentence punctuations, contextual rules, or common abbreviations) to determine likely sentence boundaries. Three chunks are produced, each ending at the periods.

You can use this technique to keep your text intact for chunks that contain many split sentences. Otherwise, the text may lose semantic context and may not be useful for queries that target specific information.


Oracle AI Vector Search stores and indexes vector embeddings for fast retrieval and similarity search.
About Oracle AI Vector Search
Vector Indexes are a new classification of specialized indexes
that are designed for Artificial Intelligence (AI) workloads that allow you
to query data based on semantics, rather than keywords.
Why Use Oracle AI Vector Search?
The biggest benefit of Oracle AI Vector Search is that semantic search
on unstructured data can be combined with relational search on business
data in one single system.

Syntax:

```
SELECT C.*
FROM documentation_tab D, VECTOR_CHUNKS(D.text BY words MAX 40 OVERLAP 0
                           SPLIT BY sentence LANGUAGE american NORMALIZE
NONE) C;
```

Output:

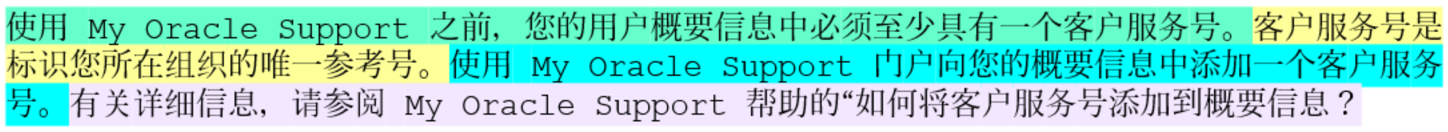
```
CHUNK_OFFSET CHUNK_LENGTH CHUNK_TEXT
-----------------------------------------------------------------------------
---------------------
1            102          Oracle AI Vector Search stores and indexes vector
embeddings for fast retrieval and similarity search.

109          228          About Oracle AI Vector Search
                          Vector Indexes are a new classification of
specialized indexes that are designed for Artificial
                          Intelligence (AI) workloads that allow you to
query data based on semantics, rather than keywords.

343         203          Why Use Oracle AI Vector Search?
                          The biggest benefit of Oracle AI Vector Search is
that semantic search on unstructured data can be
```

```
                          combined with relational search on business
data in one single system.
```

Example 3-16 BY words MAX 40 OVERLAP 0 SPLIT BY sentence LANGUAGE Simplified Chinese

In continuation with the preceding example, this example uses a Simplified Chinese text as the input to specify language-specific sentence chunking.

The output contains four chunks, each ending at the periods:



使用 My Oracle Support 之前，您的用户概要信息中必须至少具有一个客户服务号。客户服务号是标识您所在组织的唯一参考号。使用 My Oracle Support 门户向您的概要信息中添加一个客户服务号。有关详细信息，请参阅 My Oracle Support 帮助的“如何将客户服务号添加到概要信息？

For the purpose of clarity, in this example, `documentation_tab` is a `CLOB` inserted with the following `ChineseDoc.txt` document:

```
使用 My Oracle Support 之前，您的用☒概要信息中必☒至少具有一个客☒服☒号。客☒服
☒号是
☒☒您所在☒☒的唯一参考号。使用 My Oracle Support ☒☒向您的概要信息中添加一个客
☒服☒
号。有关☒☒信息，☒参☒ My Oracle Support 帮助的‟如何将客☒服☒号添加到概要信息？
```

Perform the chunking operation as follows:

```
-- create a relational table

DROP TABLE IF EXISTS documentation_tab;
CREATE TABLE documentation_tab (
    id   NUMBER,
    text CLOB);

-- create a local directory and store the document into the table

CREATE OR REPLACE DIRECTORY VEC_DUMP AS '/my_local_dir/';
CREATE OR REPLACE PROCEDURE my_clob_from_file(
    p_dir in varchar2,
    p_file in varchar2,
    p_id in number
  ) AS
  dest_loc CLOB;
  v_bfile bfile := null;
  v_lang_context number := dbms_lob.default_lang_ctx;
  v_dest_offset integer := 1;
  v_src_offset integer := 1;
  v_warning number;
BEGIN
        insert into documentation_tab values(p_id,empty_clob())
returning text
        into dest_loc;
```

```
                v_bfile := BFileName(p_dir, p_file);

                dbms_lob.open(v_bfile, dbms_lob.lob_readonly);
                dbms_lob.loadClobFromFile(
                                dest_loc,
                                v_bfile,
                                dbms_lob.lobmaxsize,
                                v_dest_offset,
                                v_src_offset,
                                873,
                                v_lang_context,
                                v_warning);
        dbms_lob.close(v_bfile);
END my_clob_from_file;
/

show errors;

-- transform clob into chunks

exec my_clob_from_file('VEC_DUMP', 'ChineseDoc.txt', 1);

SELECT rownum as id, C.chunk_offset pos, C.chunk_length as siz,
       REPLACE(SUBSTR(C.chunk_text,1,15),CHR(10),'_') as beg,
       '...' as rng,
       REPLACE(SUBSTR(C.chunk_text,-15),CHR(10),'_') as end
FROM documentation_tab D, VECTOR_CHUNKS(to_char(D.text) BY words
                                 MAX 40
                                 OVERLAP 0
                                 SPLIT BY sentence
                                 LANGUAGE "simplified chinese"
                                 NORMALIZE none) C;
```

Output:

```
ID   POS  SIZ  BEG                             RNG END
---- ---- ---- ------------------------------ --- -------------------------
   1    1  103 使用 My Oracle Su               ... 中必⊠至少具有一个客⊠服⊠号。
   2  104   60 客⊠服⊠号是⊠⊠您所在⊠⊠的唯       ... 是⊠⊠您所在⊠⊠的唯一参考号。
   3  164   85 使用 My Oracle Su               ... 概要信息中添加一个客⊠服⊠号。
   4  249  109 有关⊠⊠信息，⊠参⊠ My O          ... 何将客⊠服⊠号添加到概要信息？
```

Related Topics

- VECTOR_CHUNKS
- UTL_TO_CHUNKS

Generate Text for a Prompt: PL/SQL Example

In this example, you can see how to generate text for a given prompt by accessing third-party text generation models.

A prompt can be an input string (such as a question that you ask an LLM or a command), and can include results from a search.

You can use the described functions either from the `DBMS_VECTOR` or `DBMS_VECTOR_CHAIN` package, depending on your use case.

To generate text using "`What is Oracle Text?`" as the prompt:

1. Start SQL*Plus and connect to Oracle Database as a local test user.
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`, to a pluggable database (PDB) within your multitenant container database (CDB):

      ```
      conn sys/password@CDB_PDB as sysdba


      CREATE TABLESPACE tbs1
      DATAFILE 'tbs5.dbf' SIZE 20G AUTOEXTEND ON
      EXTENT MANAGEMENT LOCAL
      SEGMENT SPACE MANAGEMENT AUTO;
      ```

   b. Create a local test user (`docuser`) and grant necessary privileges:

      ```
      DROP USER docuser cascade;


      CREATE USER docuser identified by docuser DEFAULT TABLESPACE
      tbs1 quota unlimited on tbs1;


      GRANT DB_DEVELOPER_ROLE, create credential to docuser;
      ```

   c. Connect to Oracle Database as the test user and alter the environment settings for your session:

      ```
      CONN docuser/password@CDB_PDB


      SET ECHO ON
      SET FEEDBACK 1
      SET NUMWIDTH 10
      SET LINESIZE 80
      SET TRIMSPOOL ON
      SET TAB OFF
      SET PAGESIZE 10000
      SET LONG 10000
      ```

d. Set the HTTP proxy server, if configured:

```
EXEC UTL_HTTP.SET_PROXY('<proxy-hostname>:<proxy-port>');
```

e. Grant connect privilege for a host using the `DBMS_NETWORK_ACL_ADMIN` procedure. This example uses `*` to allow any host. However, you can explicitly specify each host that you want to connect to.

```
BEGIN
  DBMS_NETWORK_ACL_ADMIN.APPEND_HOST_ACE(
    host => '*',
    ace => xs$ace_type(privilege_list => xs$name_list('connect'),
                       principal_name => 'docuser',
                       principal_type => xs_acl.ptype_db));
END;
/
```

2. Set up your credentials for the REST provider that you want to access and then call `UTL_TO_GENERATE_TEXT`:

   - **Using Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI**:

     a. Call `CREATE_CREDENTIAL` to create and store a credential.

     Cohere, Google AI, Hugging Face, OpenAI, and Vertex AI require the following authentication parameter:

     ```
     { "access_token": "<access token>" }
     ```

     You will later refer to this credential name when declaring JSON parameters for the `UTL_TO_GENERATE_TEXT` call.

     ```
     exec dbms_vector_chain.drop_credential('<credential name>');


     declare
       jo json_object_t;
     begin
       jo := json_object_t();
       jo.put('access_token', '<access token>');
       dbms_vector_chain.create_credential(
         credential_name   => '<credential name>',
         params            => json(jo.to_string));
     end;
     /
     ```

     Replace the `access_token` and `credential_name` values. For example:

     ```
     declare
       jo json_object_t;
     begin
       jo := json_object_t();
       jo.put('access_token', 'AbabA1B123aBc123AbabAb123a1a2ab');
       dbms_vector_chain.create_credential(
         credential_name   => 'HF_CRED',
         params            => json(jo.to_string));
     ```

```
end;
/
```

b. Call `UTL_TO_GENERATE_TEXT`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for text generation service>",
  "model": "<REST provider text generation model name>"
}';

select dbms_vector_chain.utl_to_generate_text(
 'What is Oracle Text?',json(:params)) from dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  output clob;
begin
  input := 'What is Oracle Text?';

  params := '
{
  "provider": "<REST provider>",
  "credential_name": "<credential name>",
  "url": "<REST endpoint URL for text generation service>",
  "model": "<REST provider text generation model name>"
}';

  output := dbms_vector_chain.utl_to_generate_text(input,
json(params));
  dbms_output.put_line(output);
  if output is not null then
    dbms_lob.freetemporary(output);
  end if;
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `provider`, `credential_name`, `url`, and `model` values. Optionally, you can specify additional REST provider parameters.

Cohere example:

```
{
  "provider": "Cohere",
  "credential_name": "COHERE_CRED",
  "url": "https://api.cohere.example.com/generateText",
  "model": "generate-text-model"
}
```

Google AI example:

```
{
  "provider": "googleai",
  "credential_name": "GOOGLEAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "generate-text-model"
}
```

Hugging Face example:

```
{
  "provider": "huggingface",
  "credential_name": "HF_CRED",
  "url": "https://api.huggingface.example.com/models/",
  "model": "generate-text-model",
  "wait_for_model": "true"
}
```

OpenAI example:

```
{
  "provider": "openai",
  "credential_name": "OPENAI_CRED",
  "url": "https://api.openai.example.com",
  "model": "generate-text-model",
  "max_tokens": 60,
  "temperature": 1.0
}
```

Vertex AI example:

```
{
  "provider": "vertexai",
  "credential_name":"VERTEXAI_CRED",
  "url": "https://googleapis.example.com/models/",
  "model": "generate-text-model",
  "generation_config": {
    "temperature": 0.9,
    "topP": 1,
    "candidateCount": 1,
    "maxOutputTokens": 256
  }
}
```

- **Using Generative AI**:

  a. Call `CREATE_CREDENTIAL` to create and store an OCI credential (`OCI_CRED`).

     Generative AI requires the following authentication parameters:

     ```
     {
     "user_ocid": "<user ocid>",
     "tenancy_ocid": "<tenancy ocid>",
     "compartment_ocid": "<compartment ocid>",
     "private_key": "<private key>",
     "fingerprint": "<fingerprint>"
     }
     ```

     You will later refer to this credential name when declaring JSON parameters for the `UTL_TO_GENERATE_TEXT` call.

     > **Note:**
     >
     > The generated private key may appear as:
     >
     > ```
     > -----BEGIN RSA PRIVATE KEY-----
     > <private key string>
     > -----END RSA PRIVATE KEY-----
     > ```
     >
     > You pass the *`<private key string>`* value (excluding the `BEGIN` and `END` lines), either as a single line or as multiple lines.

     ```
     exec dbms_vector_chain.drop_credential('OCI_CRED');


     declare
       jo json_object_t;
     begin
       jo := json_object_t();
       jo.put('user_ocid','<user ocid>');
       jo.put('tenancy_ocid','<tenancy ocid>');
       jo.put('compartment_ocid','<compartment ocid>');
       jo.put('private_key','<private key>');
       jo.put('fingerprint','<fingerprint>');
       dbms_output.put_line(jo.to_string);
       dbms_vector_chain.create_credential(
         credential_name   => 'OCI_CRED',
         params            => json(jo.to_string));
     end;
     /
     ```

Replace all the authentication parameter values. For example:

```
declare
  jo json_object_t;
begin

  -- create an OCI credential
  jo := json_object_t();

jo.put('user_ocid','ocid1.user.oc1..aabbalbbaa1112233aabbaabb111122
2aa1111bb');

jo.put('tenancy_ocid','ocid1.tenancy.oc1..aaaaalbbbb1112233aaaabbaa
1111222aaa111a');

jo.put('compartment_ocid','ocid1.compartment.oc1..ababalabab1112233
abababab1111222aba11ab');

jo.put('private_key','AAAaaaBBB11112222333...AAA111AAABBB222aaa1a/
+');

jo.put('fingerprint','01:1a:a1:aa:12:a1:12:1a:ab:12:01:ab:a1:12:ab:
1a');
  dbms_output.put_line(jo.to_string);
  dbms_vector_chain.create_credential(
    credential_name   => 'OCI_CRED',
    params            => json(jo.to_string));
end;
/
```

b. Call `UTL_TO_GENERATE_TEXT`:

```
-- select example

var params clob;
exec :params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for text generation service>",
  "model": "<REST provider text generation model name>"
}';

select dbms_vector_chain.utl_to_generate_text(
 'What is Oracle Text?',json(:params)) from dual;

-- PL/SQL example

declare
  input clob;
  params clob;
  output clob;
begin
  input := 'What is Oracle Text?';
  params := '
{
  "provider": "ocigenai",
  "credential_name": "OCI_CRED",
  "url": "<REST endpoint URL for text generation service>",
  "model": "<REST provider text generation model name>"
}';

  output := dbms_vector_chain.utl_to_generate_text(input,
json(params));
  dbms_output.put_line(output);
  if output is not null then
    dbms_lob.freetemporary(output);
  end if;
exception
  when OTHERS THEN
    DBMS_OUTPUT.PUT_LINE (SQLERRM);
    DBMS_OUTPUT.PUT_LINE (SQLCODE);
end;
/
```

Replace the `url` and `model` values. Optionally, you can specify additional REST provider-specific parameters.

For example:

```
{
  "provider": "OCIGenAI",
  "credential_name": "GENAI_CRED",
  "url": "https://generativeai.oci.example.com/generateText",
  "model": "generate-text-model",
  "inferenceRequest": {
    "maxTokens": 300,
    "temperature": 1
  }
}
```

The generated text appears as follows:

```
BMS_VECTOR_CHAIN.UTL_TO_GENERATE_TEXT(:INPUT,JSON(:PARAMS))
--------------------------------------------------------------------
------------
Oracle Text is a powerful tool that enhances Oracle Database with
integrated
text mining and text analytics capabilities.

It enables users to extract valuable insights and make informed
decisions by
analyzing unstructured text data stored within the database.

Here are some enhanced capabilities offered by Oracle Text:

1. Full-Text Search: Enables powerful and rapid full-text searches
across large
collections of documents. This helps users find relevant
```

```
information quickly
and effectively, even within massive datasets.

2. Natural Language Processing: Implements advanced language processing
techn
iques to analyze text and extract meaningful information. This includes
capabilities
like tokenization, stemming, lemmatization, and part-of-speech tagging,
which collectively facilitate efficient text processing and understanding.

3. Sentiment Analysis: Provides a deeper understanding of sentiment
expressed
 in text. It enables businesses to automatically analyze customer
opinions, feed
back, and reviews, helping them gain valuable insights into customer
sentiment,
satisfaction levels, and potential trends.

4. Entity Recognition: Automatically identifies and categorizes entities
with
in text, such as names of people, organizations, locations, or any other
specific
terms of interest. This is useful in applications like customer
relationship
management, where linking relevant information to individuals or
organizations is
crucial.

5. Contextual Analysis: Delivers insights into the context and
relationships
between entities and concepts in textual data. It helps organizations
better und
erstand the broader implications and associations between entities,
facilitating
 a deeper understanding of their data.

These features collectively empower various applications, enhancing the
function
ality of the Oracle Database platform to allow businesses and
organizations to
derive maximum value from their unstructured text data.

Let me know if you'd like to dive deeper into any of these specific
capabilities
, or if there are other aspects of Oracle Text you'd like to explore
further.
```

This example uses the default settings for each provider. For detailed information on additional parameters, refer to your third-party provider's documentation.

Related Topics

- DBMS_VECTOR Package
- DBMS_VECTOR_CHAIN Package

4

Store Vector Embeddings

You store the resulting vector embeddings and associated unstructured data with your relational business data in Oracle Database.

- Create Tables Using the VECTOR Data Type
  You can declare a table's column as a VECTOR data type.
- Insert Vectors in a Database Table Using the INSERT Statement
  Once you create a table with a VECTOR data type column, you can directly insert vectors into the table using the INSERT statement.
- Load Vector Data Using SQL*Loader
  Use these examples to understand how you can load character and binary vector data.
- Unload and Load Vectors Using Oracle Data Pump
  Starting with Oracle Database 23ai, Oracle Data Pump enables you to use multiple components to load and unload vectors to databases.

Create Tables Using the VECTOR Data Type

You can declare a table's column as a VECTOR data type.

The following command shows a simple example:

```
CREATE TABLE my_vectors (id NUMBER, embedding VECTOR);
```

In this example, you don't have to specify the number of dimensions or their format, which are both optional. If you don't specify any of them, you can enter vectors of different dimensions with different formats. This is a simplification to help you get started with using vectors in Oracle Database.

Note:

Such vectors typically arise from different embedding models. Vectors from different models (providing a different semantic landscape) are not comparable for use in similarity search.

Here's a more complex example that imposes more constraints on what you can store:

```
CREATE TABLE my_vectors (id NUMBER, embedding VECTOR(768, INT8)) ;
```

In this example, each vector that is stored:

- Must have 768 dimensions, and
- Each dimension will be formatted as an INT8.

The number of dimensions must be strictly greater than zero with no practical upper limit.

The possible dimension formats are:

- `INT8` (8-bit integers)
- `FLOAT32` (32-bit IEEE floating-point numbers)
- `FLOAT64` (64-bit IEEE floating-point numbers)

Oracle Database automatically casts the values as needed.

The following table guides you through the possible declaration format for a `VECTOR` data type:

Possible Declaration Format	Explanation
`VECTOR`	Vectors can have an arbitrary number of dimensions and formats.
`VECTOR(*, *)`	Vectors can have an arbitrary number of dimensions and formats. `VECTOR` and `VECTOR(*,*)` are equivalent.
`VECTOR`(number_of_dimensions, *)	Vectors must all have the specified number of dimensions or an error is thrown. Every vector will have its dimensions stored without format modification.
`VECTOR`(number_of_dimensions)	Vectors must all have the specified number of dimensions or an error is thrown. Every vector will have its dimensions stored without format modification. `VECTOR`(number_of_dimensions, *) and `VECTOR`(number_of_dimensions) are equivalent.
`VECTOR`(*, dimension_element_format)	Vectors can have an arbitrary number of dimensions, but their format will be up-converted or down-converted to the specified dimension_element_format (`INT8`, `FLOAT32`, or `FLOAT64`).

A vector can be `NULL` but its dimensions cannot (for example, you cannot have a `VECTOR` with a `NULL` dimension such as `[1.1, NULL, 2.2]`).

The following SQL*Plus code example shows how the system interprets various vector definitions:

```
CREATE TABLE my_vect_tab (
     v1 VECTOR(3, FLOAT32),
     v2 VECTOR(2, FLOAT64),
     v3 VECTOR(1, INT8),
     v4 VECTOR(1, *),
     v5 VECTOR(*, FLOAT32),
     v6 VECTOR(*, *),
     v7 VECTOR
   );

Table created.

DESC my_vect_tab;
 Name                           Null?    Type
 --------------------------- -------- ----------------------------
 V1                                    VECTOR(3 , FLOAT32)
 V2                                    VECTOR(2 , FLOAT64)
 V3                                    VECTOR(1 , INT8)
 V4                                    VECTOR(1 , *)
 V5                                    VECTOR(* , FLOAT32)
 V6                                    VECTOR(* , *)
 V7                                    VECTOR(* , *)
```

You currently cannot define `VECTOR` columns in/as:

- External Tables
- IOTs (neither as Primary Key nor as non-Key column)
- Clusters/Cluster Tables
- Global Temp Tables
- (Sub)Partitioning Key
- Primary Key
- Foreign Key
- Unique Constraint
- Check Constraint
- Default Value
- Modify Column
- MSSM tablespace (only SYS user can create VECTORs as Basicfiles in MSSM tablespace)
- CQN queries
- Non-vector indexes such as B-tree, Bitmap, Reverse Key, Text, Spatial indexes, etc

Oracle Database does not support the following SQL constructs with VECTOR columns:

- Distinct, Count Distinct
- Order By, Group By
- Join condition
- Comparison operators (e.g. >, <, =) etc

Insert Vectors in a Database Table Using the INSERT Statement

Once you create a table with a `VECTOR` data type column, you can directly insert vectors into the table using the `INSERT` statement.

The following examples assume you have already created vectors and know their values.

Here is a simple example:

```
DROP TABLE galaxies PURGE;
CREATE TABLE galaxies (id NUMBER, name VARCHAR2(50), doc VARCHAR2(500),
embedding VECTOR);

INSERT INTO galaxies VALUES (1, 'M31', 'Messier 31 is a barred spiral galaxy
in the Andromeda constellation which has a lot of barred spiral
galaxies.', '[0,2,2,0,0]');
INSERT INTO galaxies VALUES (2, 'M33', 'Messier 33 is a spiral galaxy
in the Triangulum constellation.', '[0,0,1,0,0]');
INSERT INTO galaxies VALUES (3, 'M58', 'Messier 58 is an intermediate
barred spiral galaxy in the Virgo constellation.', '[1,1,1,0,0]');
INSERT INTO galaxies VALUES (4, 'M63', 'Messier 63 is a spiral galaxy
in the Canes Venatici constellation.', '[0,0,1,0,0]');
INSERT INTO galaxies VALUES (5, 'M77', 'Messier 77 is a barred spiral
galaxy in the Cetus constellation.', '[0,1,1,0,0]');
INSERT INTO galaxies VALUES (6, 'M91', 'Messier 91 is a barred spiral
galaxy in the Coma Berenices constellation.', '[0,1,1,0,0]');
INSERT INTO galaxies VALUES (7, 'M49', 'Messier 49 is a giant
elliptical galaxy in the Virgo constellation.', '[0,0,0,1,1]');
INSERT INTO galaxies VALUES (8, 'M60', 'Messier 60 is an elliptical
galaxy in the Virgo constellation.', '[0,0,0,0,1]');
INSERT INTO galaxies VALUES (9, 'NGC1073', 'NGC 1073 is a barred
spiral galaxy in Cetus constellation.', '[0,1,1,0,0]');
COMMIT;
```

Here is a more sophisticated example:

```
DROP TABLE doc_queries PURGE;
CREATE TABLE doc_queries (id NUMBER, query VARCHAR2(500), embedding
VECTOR);

DECLARE
  e CLOB;
BEGIN
e:=
'[-7.73346797E-002,1.09683955E-002,4.68435362E-002,2.57333983E-002,6.95
586428E-00'||
'2,-2.43412293E-002,-7.25011379E-002,6.66433945E-002,3.78751606E-002,-2
.22354475E'||
'-002,3.02388351E-002,9.36625451E-002,-1.65204913E-003,3.50606232E-003,
-5.4773859'||
'7E-002,-7.5879097E-002,-2.72218436E-002,7.01764375E-002,-1.32512336E-0
03,3.14728'||
'022E-002,-1.39147148E-001,-7.52705336E-002,2.62449421E-002,1.91645715E
-002,4.055'||
'73137E-002,5.83701171E-002,-3.26474942E-002,2.0509012E-002,-3.81141738
E-003,-7.1'||
'8656182E-002,-1.95893757E-002,-2.56917924E-002,-6.57705888E-002,-4.391
17625E-002'||
',-6.82357177E-002,1.26592368E-001,-3.46683599E-002,1.07687116E-001,-3.
96954492E-'||
'002,-9.06721968E-003,-2.4109887E-002,-1.29214963E-002,-4.82468568E-002
,-3.872307'||
'76E-002,5.13443872E-002,-1.40985977E-002,-1.87066793E-002,-1.11725368E
-002,9.367'||
'76772E-002,-6.39425665E-002,3.13162468E-002,8.61801133E-002,-5.5481784
E-002,4.13'||
'125418E-002,2.0447813E-002,5.03717586E-002,-1.73418857E-002,3.94522659
E-002,-7.2'||
'6833269E-002,3.13266069E-002,1.2377765E-002,7.64856935E-002,-3.77447419E-002
,-6.'||
'41075056E-003,1.1455299E-001,1.75497644E-002,4.64923214E-003,1.89623125E-002
,9.1'||
'3506597E-002,-8.22509527E-002,-1.28537193E-002,1.495138E-002,-3.22528258E-00
2,-4'||
'.71280375E-003,-3.15563753E-003,2.20409594E-002,7.77796134E-002,-1.927099E-0
02,-'||
'1.24283969E-001,4.69769612E-002,1.78121701E-002,1.67152807E-002,-3.83916795E
-002'||
',-1.51029453E-002,2.10864041E-002,6.86845928E-002,-7.4719809E-002,1.17681816
E-00'||
'3,3.93113159E-002,6.04066066E-002,8.55340436E-002,3.68878953E-002,2.41579115
E-00'||
'2,-5.92489541E-002,-1.21883564E-002,-1.77226216E-002,-1.96259264E-002,8.5123
6377'||
'E-003,1.43039867E-001,2.62829307E-002,2.96348184E-002,1.92485824E-002,7.6656
7141'||
'E-002,-1.18600562E-001,3.01779062E-002,-5.88010997E-002,7.07774982E-002,-6.6
0426'||
'617E-002,6.44619241E-002,1.29240509E-002,-2.51785964E-002,2.20869959E-004,-2
.514'||
'38171E-002,5.52265197E-002,8.65883753E-002,-1.83726232E-002,-8.13263431E-002
,1.1'||
'6624301E-002,1.63392909E-002,-3.54643688E-002,2.05128491E-002,4.67337575E-00
3,1.'||
'20488718E-001,-4.89500947E-002,-3.80397178E-002,6.06209273E-003,-1.37961926E
-002'||
',4.68355882E-031,3.35873142E-002,6.20040558E-002,2.13472452E-002,-1.87379227
E-00'||
'3,-5.83158981E-004,-4.04266678E-002,2.40761992E-002,-1.93725452E-002,9.37637
24E-'||
'002,-3.02913114E-002,7.67844869E-003,6.11112304E-002,6.02455214E-002,-6.3885
5845'||
'E-002,-8.03523697E-003,2.08786246E-003,-7.45898336E-002,8.74964818E-002,-5.0
2371'||
'937E-002,-4.99385223E-003,3.37120108E-002,8.99377018E-002,1.09540671E-001,5.
8501'||
'102E-002,1.71627291E-002,-3.26152593E-002,8.36912021E-002,5.05600758E-002,-9
.737'||
'63615E-002,-1.40264994E-002,-2.07926836E-002,-4.20163684E-002,-5.97197041E-0
02,1'||
'.32461395E-002,2.26361351E-003,8.1473738E-002,-4.29272018E-002,-3.86809185E-
002,'||
'-8.24682564E-002,-3.89646105E-002,1.9992901E-002,2.07321253E-002,-1.74706057
E-00'||
'2,4.50415723E-003,4.43851873E-002,-9.86309871E-002,-7.68082142E-002,-4.53814
305E'||
'-003,-8.90906602E-002,-4.54972908E-002,-5.71065396E-002,2.10020249E-003,1.22
4947'||
'07E-002,-6.70659095E-002,-6.52298108E-002,3.92126441E-002,4.33384106E-002,4.
3899'||
'6181E-002,5.78813367E-002,2.95345876E-002,4.68395352E-002,9.15119275E-002,-9
.629'||
'58392E-003,-5.96637605E-003,1.58674959E-002,-6.74034096E-003,-6.00510836E-00
```

```
2,2.'||
'67188111E-003,-1.10706768E-003,-6.34015873E-002,-4.80389707E-002,6.845
34572E-003'||
',-1.1547043E-002,-3.44865513E-003,1.18979132E-002,-4.31232266E-002,-5.
9022788E-0'||
'02,4.87607308E-002,3.95954074E-003,-7.95252472E-002,-1.82770658E-002,1
.18264249E'||
'-002,-3.79164703E-002,3.87993976E-002,1.09805465E-002,2.29136664E-002,
-7.2278082'||
'4E-002,-5.31538352E-002,6.38669729E-002,-2.47980515E-003,-9.6999377E-0
02,-3.7566'||
'7699E-002,4.06541862E-002,-1.69874367E-003,5.58868013E-002,-1.80723771
E-033,-6.6'||
'5985467E-003,-4.45010923E-002,1.77929532E-002,-4.8369132E-002,-1.49722
975E-002,-'||
'3.97582203E-002,-7.05247298E-002,3.89178023E-002,-8.26886389E-003,-3.9
1006246E-0'||
'02,-7.02963024E-002,-3.91333885E-002,1.76661201E-002,-5.09723537E-002,
2.37749107'||
'E-002,-1.83419678E-002,-1.2693027E-002,-1.14232123E-001,-6.68751821E-0
02,7.52167'||
'869E-003,-9.94713791E-003,6.03599809E-002,6.61353692E-002,3.70595567E-
002,-2.019'||
'52495E-002,-2.40410417E-002,-3.36526595E-002,6.20064288E-002,5.5027995
3E-002,-2.'||
'68641673E-002,4.35859226E-002,-4.57317568E-002,2.76936609E-002,7.88119
733E-002,-'||
'4.78852056E-002,1.08523415E-002,-6.43479973E-002,2.0192951E-002,-2.095
38229E-002'||
',-2.2202393E-002,-1.0728148E-003,-3.09607089E-002,-1.67067181E-002,-6.
03572279E-'||
'002,-1.58187654E-002,3.45828459E-002,-3.45360823E-002,-4.4002533E-003,
1.77463517'||
'E-002,6.68234832E-004,6.14458732E-002,-5.07084019E-002,-1.21073434E-00
2,4.195981'||
'85E-002,3.69152687E-002,1.09461844E-002,1.83413982E-001,-3.89185362E-0
02,-5.1846'||
'0497E-002,-8.71620141E-003,-1.17692262E-001,4.04785499E-002,1.07505821
E-001,1.41'||
'624091E-002,-2.57720836E-002,2.6652012E-002,-4.50568087E-002,-3.341103
35E-002,-1'||
'.11387551E-001,-1.29796984E-003,-6.51671961E-002,5.36890551E-002,1.070
2607E-001,'||
'-2.34011523E-002,3.97406481E-002,-1.01149324E-002,-9.95831117E-002,-4.
40197848E-'||
'002,6.88989647E-003,4.85475454E-003,-3.94048765E-002,-3.6099229E-002,-
5.4075513E'||
'-002,8.58292207E-002,1.0697281E-002,-4.70785573E-002,-2.96272673E-002,
-9.4919120'||
'9E-003,1.57316476E-002,-5.4926388E-002,6.49022609E-002,2.55531631E-002
,-1.839057'||
'17E-002,4.06873561E-002,4.74951901E-002,-1.22502812E-033,-4.6441108E-0
02,3.74079'||
'868E-002,9.14599106E-004,6.09740615E-002,-7.67391697E-002,-6.32521287E
-002,-2.17'||
'353106E-002,2.45231949E-003,1.50869079E-002,-4.96984981E-002,-3.40828523E-00
2,8.'||
'09691194E-003,3.31339166E-002,5.41345142E-002,-1.16213948E-001,-2.49572527E-
002,'||
'5.00682592E-002,5.90037219E-002,-2.89178211E-002,8.01460445E-003,-3.41945067
E-00'||
'2,-8.60121697E-002,-6.20261126E-004,2.26721354E-002,1.28968194E-001,2.876553
68E-'||
'002,-2.20255274E-002,2.7228903E-002,-1.12029864E-002,-3.20301466E-002,4.9807
9099'||
'E-002,2.89051589E-002,2.413591E-002,3.64605561E-002,6.26017479E-003,6.546328
96E-'||
'002,1.11282602E-001,-3.60428065E-004,1.95987038E-002,6.16615731E-003,5.93593
046E'||
'-002,1.50377362E-003,2.95319762E-002,2.56325547E-002,-1.72190219E-002,-6.581
6819'||
'7E-002,-4.08149995E-002,2.7983617E-002,-6.80195764E-002,-3.52494679E-002,-2.
9840'||
'0577E-002,-3.04043181E-002,-1.9352382E-002,5.49411364E-002,8.74160081E-002,5
.614'||
'25127E-002,-5.60747795E-002,-3.43311466E-002,9.83581021E-002,2.01142877E-002
,1.3'||
'193069E-002,-3.22583504E-002,8.54402035E-002,-2.20514946E-002]';

INSERT INTO doc_queries VALUES (13, 'different methods of backup and
recovery', e);
COMMIT;
END;
/
```

You can also generate vectors by calling services outside the database or generate vectors directly from within the database after you have imported pretrained embedding models.

See Also:

- Import Pretrained Models in ONNX Format for Vector Generation Within the Database
- Convert Text String to Embedding

Load Vector Data Using SQL*Loader

Use these examples to understand how you can load character and binary vector data.

SQL*Loader supports loading `VECTOR` columns from character data and binary floating point array `fvec` files. The format for `fvec` files is that each binary 32-bit floating point array is preceded by a four (4) byte value, which is the number of elements in the vector. There can be multiple vectors in the file, possibly with different dimensions. Export and import of a table with vector datatype columns is supported in all the modes (FULL, SCHEMA, TABLES) using all the available methods (access_method=direct_path, access_method=external_table, access_method=automatic) for unloading/loading data.

- Load Character Vector Data Using SQL*Loader Example
  In this example, you can see how to use SQL*Loader to load vector data into a five-dimension vector space.
- Load Binary Vector Data Using SQL*Loader Example
  In this example, you can see how to use SQL*Loader to load binary vector data files.

Load Character Vector Data Using SQL*Loader Example

In this example, you can see how to use SQL*Loader to load vector data into a five-dimension vector space.

Let's imagine we have the following text documents classifying galaxies by their types:

- **DOC1**: "Messier 31 is a barred spiral galaxy in the Andromeda constellation which has a lot of barred spiral galaxies."
- **DOC2**: "Messier 33 is a spiral galaxy in the Triangulum constellation."
- **DOC3**: "Messier 58 is an intermediate barred spiral galaxy in the Virgo constellation."
- **DOC4**: "Messier 63 is a spiral galaxy in the Canes Venatici constellation."
- **DOC5**: "Messier 77 is a barred spiral galaxy in the Cetus constellation."
- **DOC6**: "Messier 91 is a barred spiral galaxy in the Coma Berenices constellation."
- **DOC7**: "NGC 1073 is a barred spiral galaxy in Cetus constellation."
- **DOC8**: "Messier 49 is a giant elliptical galaxy in the Virgo constellation."
- **DOC9**: "Messier 60 is an elliptical galaxy in the Virgo constellation."

You can create vectors representing the preceding galaxy's classes using the following five-dimension vector space based on the count of important words appearing in each document:

Table 4-1 Five dimension vector space

Galaxy Classes	Intermediate	Barred	Spiral	Giant	Elliptical
M31	0	2	2	0	0
M33	0	0	1	0	0
M58	1	1	1	0	0
M63	0	0	1	0	0
M77	0	1	1	0	0
M91	0	1	1	0	0
M49	0	0	0	1	1
M60	0	0	0	0	1
NGC1073	0	1	1	0	0

This naturally gives you the following vectors:

- **M31**: `[0,2,2,0,0]`
- **M33**: `[0,0,1,0,0]`

- **M58**: `[1,1,1,0,0]`
- **M63**: `[0,0,1,0,0]`
- **M77**: `[0,1,1,0,0]`
- **M91**: `[0,1,1,0,0]`
- **M49**: `[0,0,0,1,1]`
- **M60**: `[0,0,0,0,1]`
- **NGC1073**: `[0,1,1,0,0]`

You can use SQL*Loader to load this data into the `GALAXIES` database table defined as:

```
drop table galaxies purge;
create table galaxies (id number, name varchar2(50), doc varchar2(500),
embedding vector);
```

Based on the data described previously, you can create the following `galaxies_vec.csv` file:

```
1:M31:Messier 31 is a barred spiral galaxy in the Andromeda constellation
which has a lot of barred spiral galaxies.:[0,2,2,0,0]:
2:M33:Messier 33 is a spiral galaxy in the Triangulum constellation.:
[0,0,1,0,0]:
3:M58:Messier 58 is an intermediate barred spiral galaxy in the Virgo
constellation.:[1,1,1,0,0]:
4:M63:Messier 63 is a spiral galaxy in the Canes Venatici constellation.:
[0,0,1,0,0]:
5:M77:Messier 77 is a barred spiral galaxy in the Cetus constellation.:
[0,1,1,0,0]:
6:M91:Messier 91 is a barred spiral galaxy in the Coma Berenices
constellation.:[0,1,1,0,0]:
7:M49:Messier 49 is a giant elliptical galaxy in the Virgo constellation.:
[0,0,0,1,1]:
8:M60:Messier 60 is an elliptical galaxy in the Virgo constellation.:
[0,0,0,0,1]:
9:NGC1073:NGC 1073 is a barred spiral galaxy in Cetus constellation.:
[0,1,1,0,0]:
```

Here is a possible SQL*Loader control file `galaxies_vec.ctl`:

```
recoverable
LOAD DATA
infile 'galaxies_vec.csv'
INTO TABLE galaxies
fields terminated by ':'
trailing nullcols
(
id,
name char (50),
doc  char (500),
embedding char (32000)
)
```

After you have created the two files `galaxies_vec.csv` and `galaxies_vec.ctl`, you can run the following sequence of instructions directly from your favorite SQL command line tool:

```
host sqlldr vector/vector@CDB1_PDB1 control=galaxies_vec.ctl
log=galaxies_vec.log

SQL*Loader: Release 23.0.0.0.0 - Development on Thu Jan 11 19:46:21
2024
Version 23.4.0.23.00

Copyright (c) 1982, 2024, Oracle and/or its affiliates.  All rights
reserved.

Path used:      Conventional
Commit point reached - logical record count 10

Table GALAXIES2:
  9 Rows successfully loaded.

Check the log file:
  galaxies_vec.log
for more information about the load.

SQL>

select * from galaxies;

 ID NAME    DOC
EMBEDDING
--- ------  ----------------------------------------------------------
---------------------------------
  1 M31     Messier 31 is a barred spiral galaxy in the Andromeda ...
[0,2.0E+000,2.0E+000,0,0]
  2 M33     Messier 33 is a spiral galaxy in the Triangulum ...
[0,0,1.0E+000,0,0]
  3 M58     Messier 58 is an intermediate barred spiral galaxy ...
[1.0E+000,1.0E+000,1.0E+000,0,0]
  4 M63     Messier 63 is a spiral galaxy in the Canes Venatici ...
[0,0,1.0E+000,0,0]
  5 M77     Messier 77 is a barred spiral galaxy in the Cetus ...
[0,1.0E+000,1.0E+000,0,0]
  6 M91     Messier 91 is a barred spiral galaxy in the Coma ...
[0,1.0E+000,1.0E+000,0,0]
  7 M49     Messier 49 is a giant elliptical galaxy in the Virgo ...
[0,0,0,1.0E+000,1.0E+000]
  8 M60     Messier 60 is an elliptical galaxy in the Virgo ...
[0,0,0,0,1.0E+000]
  9 NGC1073 NGC 1073 is a barred spiral galaxy in Cetus ...
[0,1.0E+000,1.0E+000,0,0]

9 rows selected.

SQL>
```

Here is the resulting log file for this load (`galaxies_vec.log`):

```
cat galaxies_vec.log

SQL*Loader: Release 23.0.0.0.0 - Development on Thu Jan 11 19:46:21 2024
Version 23.4.0.23.00

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Control File:   galaxies_vec.ctl
Data File:      galaxies_vec.csv
  Bad File:     galaxies_vec.bad
  Discard File:  none specified

 (Allow all discards)

Number to load: ALL
Number to skip: 0
Errors allowed: 50
Bind array:     250 rows, maximum of 1048576 bytes
Continuation:    none specified
Path used:      Conventional

Table GALAXIES, loaded from every logical record.
Insert option in effect for this table: INSERT
TRAILING NULLCOLS option in effect

Column Name   Position   Len  Term Encl Datatype
----------- ---------- ----- ---- ---- ----------
ID               FIRST     *   :       CHARACTER
NAME              NEXT    50   :       CHARACTER
DOC               NEXT   500   :       CHARACTER
EMBEDDING         NEXT 32000   :       CHARACTER

value used for ROWS parameter changed from 250 to 31


Table GALAXIES2:
  9 Rows successfully loaded.
  0 Rows not loaded due to data errors.
  0 Rows not loaded because all WHEN clauses were failed.


Space allocated for bind array:                1017234 bytes(31 rows)
Read   buffer bytes: 1048576

Total logical records skipped:          0
Total logical records read:             9
Total logical records rejected:         0
Total logical records discarded:        1

Run began on Thu Jan 11 19:46:21 2024
Run ended on Thu Jan 11 19:46:24 2024

Elapsed time was:     00:00:02.43
```

```
CPU time was:          00:00:00.03
$
```

Note:

This example uses `embedding char (32000)` vectors. For very large vectors, you can use the `LOBFILE` feature

Related Topics

- Loading LOB Data from LOBFILEs

Load Binary Vector Data Using SQL*Loader Example

In this example, you can see how to use SQL*Loader to load binary vector data files.

The vectors in a binary (`fvec`) file are stored in raw 32-bit Little Endian format.

Each vector takes 4+*d**4 bytes for the `.fvecs` file where the first 4 bytes indicate the dimensionality (*d*) of the vector (that is, the number of dimensions in the vector) followed by *d**4 bytes representing the vector data, as described in the following table:

Table 4-2 Fields for Vector Dimensions and Components

Field	Field Type	Description
d	int	The vector dimension
components	array of floats	The vector components

For binary `fvec` files, they must be defined as follows:

- You must specify `LOBFILE`.
- You must specify the syntax format `fvecs` to indicate that the dafafile contains binary dimensions.
- You must specify that the datafile contains raw binary data (`raw`).

The following is an example of a control file used to load `VECTOR` columns from binary floating point arrays using the galaxies vector example described in Understand Hierarchical Navigable Small World Indexes, but in this case importing `fvecs` data, using the control file syntax `format "fvecs"`:

Note:

SQL*Loader supports loading `VECTOR` columns from character data and binary floating point array `fvec` files. The format for `fvec` files is that each binary 32-bit floating point array is preceded by a four (4) byte value, which is the number of elements in the vector. There can be multiple vectors in the file, possibly with different dimensions.

```
LOAD DATA
infile 'galaxies_vec.csv'
INTO TABLE galaxies
fields terminated by ':'
trailing nullcols
(
id,
name char (50),
doc  char (500),
embedding lobfile (constant '/u01/data/vector/embedding.fvecs' format
"fvecs")  raw
)
```

The data contained in `galaxies_vec.csv` in this case does not have the vector data. Instead, the vector data will be read from the secondary `LOBFILE` in the `/u01/data/vector` directory (`/u01/data/vector/embedding.fvecs`), which contains the same information in `float32` floating point binary numbers, but is in `fvecs` format:

```
1:M31:Messier 31 is a barred spiral galaxy in the Andromeda constellation
which has a lot of barred spiral galaxies.:
2:M33:Messier 33 is a spiral galaxy in the Triangulum constellation.:
3:M58:Messier 58 is an intermediate barred spiral galaxy in the Virgo
constellation.:
4:M63:Messier 63 is a spiral galaxy in the Canes Venatici constellation.:
5:M77:Messier 77 is a barred spiral galaxy in the Cetus constellation.:
6:M91:Messier 91 is a barred spiral galaxy in the Coma Berenices
constellation.:
7:M49:Messier 49 is a giant elliptical galaxy in the Virgo constellation.:
8:M60:Messier 60 is an elliptical galaxy in the Virgo constellation.:
9:NGC1073:NGC 1073 is a barred spiral galaxy in Cetus constellation.:
```

Unload and Load Vectors Using Oracle Data Pump

Starting with Oracle Database 23ai, Oracle Data Pump enables you to use multiple components to load and unload vectors to databases.

Oracle Data Pump technology enables very high-speed movement of data and metadata from one database to another. Oracle Data Pump is made up of three distinct components: Command-line clients, expdp and impdp; the DBMS_DATAPUMP PL/SQL package (also known as the Data Pump API); and the DBMS_METADATA PL/SQL package (also known as the Metadata API).

Unloading and Loading a table with vector datatype columns is supported in all modes (`FULL`, `SCHEMA`, `TABLES`) using all the available access methods (`DIRECT_PATH`, `EXTERNAL_TABLE`, `AUTOMATIC`, `INSERT_AS_SELECT`).

Examples Vector Export and Import Syntax

```
expdp <username>/<password>@<Database-instance-TNS-alias>
dumpfile=<dumpfile-name>.dmp directory=<directory-name> full=y
metrics=y access_method=direct_path

expdp <username>/<password>@<Database-instance-TNS-alias>
dumpfile=<dumpfile-name>.dmp directory=<directory-name>
schemas=<schema-name> metrics=y access_method=external_table

expdp <username>/<password>@<Database-instance-TNS-alias>
dumpfile=<dumpfile-name>.dmp directory=<directory-name> tables=<schema-
name>.<table-name> metrics=y access_method=direct_path

impdp <username>/<password>@<Database-instance-TNS-alias>
dumpfile=<dumpfile-name>.dmp directory=<directory-name> metrics=y
access_method=direct_path
```

Note:

- `TABLE_EXISTS_ACTION=APPEND | TRUNCATE` can only be used with the `EXTERNAL_TABLE` access method.
- `TABLE_EXISTS_ACTION=APPEND | TRUNCATE` can load `VECTOR` column data into a `VARCHAR2` column if the conversion can fit into that `VARCHAR2`.
- `TABLE_EXISTS_ACTION=APPEND | TRUNCATE` can only load a `VECTOR` column with the source `VECTOR` data dimasion that matches that loaded `VECTOR` column's dimension. If the dimension does not match, then an error is raised.
- `TABLE_EXISTS_ACTION=REPLACE` supports any access method.
- It is not possible to use a the transportable tablespace mode with vector indexes. However, this mode supports tables with the `VECTOR` datatype.

Related Topics

- Overview of Oracle Data Pump
- DBMS_DATAPUMP
- DBMS_METADATA

5

Create Vector Indexes

You may want to create vector indexes on your vector embeddings and use these indexes for running similarity searches over huge vector spaces.

Vector indexes are a class of specialized indexing data structures that are designed to accelerate similarity searches using high-dimensional vectors. They use techniques such as clustering, partitioning, and neighbor graphs to group vectors representing similar items, which drastically reduces the search space, thereby making the search process extremely efficient.

- Size the Vector Pool
  To allow vector index creation, you must enable a new memory area stored in the SGA called the **Vector Pool**.
- Manage the Different Categories of Vector Indexes
  Learn how vector indexing methods make vector searches faster and how to enable vector indexes creation.

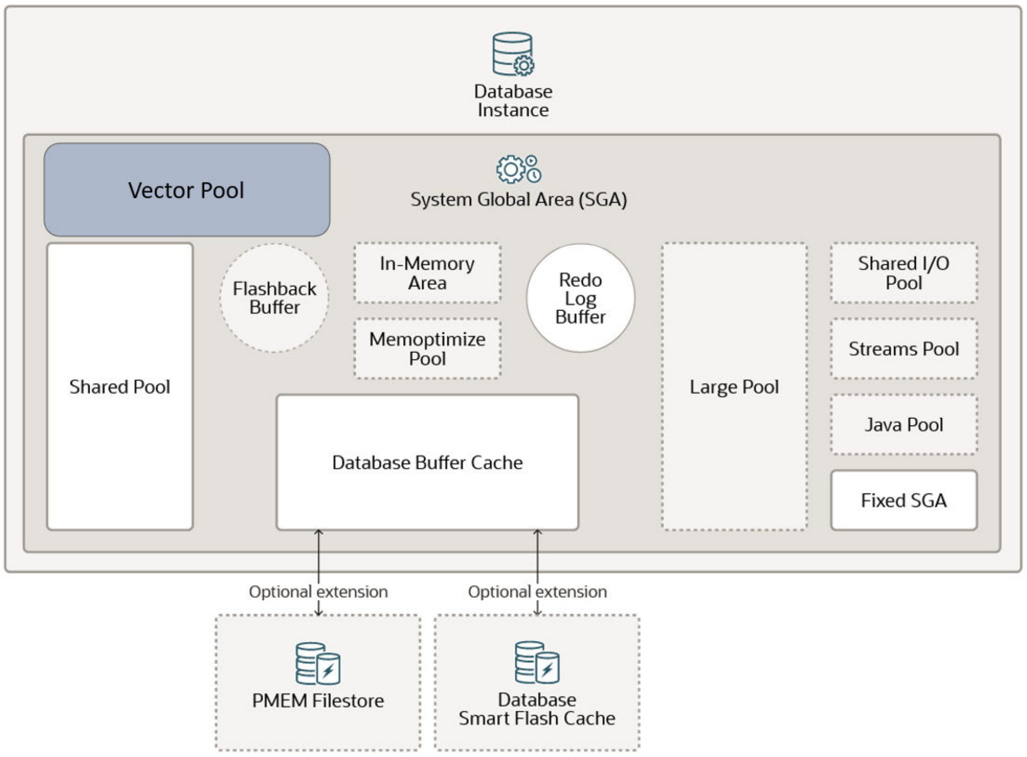
Size the Vector Pool

To allow vector index creation, you must enable a new memory area stored in the SGA called the **Vector Pool**.

The Vector Pool is a memory allocated in SGA to store Hierarchical Navigable Small World (HNSW) vector indexes and all associated metadata. It is also used to speed up Inverted Flat File (IVF) index creation as well as DML operations on base tables with IVF indexes.

Enabling a Vector Pool is illustrated in the following diagram:

Figure 5-1 Vector Pool



To size the Vector Pool, use the `VECTOR_MEMORY_SIZE` initialization parameter. You can dynamically modify this parameter at the following levels:

- At the CDB level `VECTOR_MEMORY_SIZE` specifies the current size of the Vector Pool. Reducing the parameter value will fail if there is current vector usage.
- At the PDB level `VECTOR_MEMORY_SIZE` specifies the maximum Vector Pool usage allowed by a PDB. Reducing the parameter value will be allowed even if current vector usage exceeds the new quota.

You can change the value of a parameter in a parameter file in the following ways:

- By editing an initialization parameter file. In most cases, the new value takes effect the next time you start an instance of the database.
- By issuing an `ALTER SYSTEM SET ... SCOPE=SPFILE` statement to update a server parameter file.
- By issuing an `ALTER SYSTEM RESET` statement to clear an initialization parameter value and set it back to its default value.

Here is an example of how to change the value for `VECTOR_MEMORY_SIZE` at the PDB level if you are using an SPFILE:

```
SQL> show con_name
CON_NAME
------------------------------
MYPDB1

SQL> show user
```

```
USER is "SYS"

SQL> show parameter vector_memory_size
NAME               TYPE        VALUE
------------------ ----------- -----
vector_memory_size big integer 500M

SQL> SELECT ISPDB_MODIFIABLE
  2  FROM   V$SYSTEM_PARAMETER
  3* WHERE  NAME='vector_memory_size';

ISPDB_MODIFIABLE
___________________
TRUE

SQL> ALTER SYSTEM SET vector_memory_size=1G SCOPE=BOTH;

System altered.

SQL> show parameter vector_memory_size

NAME                TYPE        VALUE
------------------- ----------- -------
vector_memory_size  big integer 1G
SQL>
```

For more information about changing initialization parameter values, see Managing Initialization Parameters Using a Server Parameter File

`V$VECTOR_MEMORY_POOL`, is the view you can query to monitor the Vector Pool.

See Also:

- Vector Memory Pool Views

Manage the Different Categories of Vector Indexes

Learn how vector indexing methods make vector searches faster and how to enable vector indexes creation.

There are two ways to make vector searches faster:

- Reduce the search scope by clustering vectors (nearest neighbors) into structures based on certain attributes and restricting the search to closest clusters.
- Reduce the vector size by reducing the number of bits representing vectors values.

Oracle AI Vector Search supports the following categories of vector indexing methods based on approximate nearest-neighbors (ANN) search:

- In-Memory Neighbor Graph Vector Index
- Neighbor Partition Vector Index

The distance function used to create and search the index should be the one recommended by the embedding model used to create the vectors. You can specify this distance function at the time of index creation or when you perform a similarity search using the `VECTOR_DISTANCE()` function. If you use a different distance function than the one used to create the index, an exact match is triggered because you cannot use the index in this case.

Note:

- Oracle AI Vector Search indexes supports the same distance metrics as the `VECTOR_DISTANCE()` function. `COSINE` is the default metric if you do not specify any metric at the time of index creation or during a similarity search using the `VECTOR_DISTANCE()` function.
- You should always define the distance metric in an index based on the distance metric used by the embedding model you are using.

- In-Memory Neighbor Graph Vector Index
  Hierarchical Navigable Small World (HNSW) is the only type of In-Memory Neighbor Graph vector index supported. HNSW graphs are very efficient indexes for vector approximate similarity search. HNSW graphs are structured using principles from small world networks along with layered hierarchical organization.
- Neighbor Partition Vector Index
  Inverted File Flat (IVF) index is the only type of Neighbor Partition vector index supported. Inverted File Flat Index (IVF Flat or simply IVF) is a partitioned-based index which balance high search quality with reasonable speed.
- Guidelines for Using Vector Indexes
  Use these guidelines to create and use Hierarchical Navigable Small World (HNSW) or Inverted File Flat (IVF) vector indexes.
- Index Accuracy Report
  The index accuracy reporting feature lets you determine the accuracy of your vector indexes.

In-Memory Neighbor Graph Vector Index

Hierarchical Navigable Small World (HNSW) is the only type of In-Memory Neighbor Graph vector index supported. HNSW graphs are very efficient indexes for vector approximate similarity search. HNSW graphs are structured using principles from small world networks along with layered hierarchical organization.

- Understand Hierarchical Navigable Small World Indexes
  The default type of index created for an In-Memory Neighbor Graph vector index is Hierarchical Navigable Small World (HNSW). Use these examples to understand how to create HNSW indexes for vector approximate similarity searches.
- Hierarchical Navigable Small World Index Syntax and Parameter
  Syntax for Hierarchical Navigable Small World Index

Understand Hierarchical Navigable Small World Indexes

The default type of index created for an In-Memory Neighbor Graph vector index is Hierarchical Navigable Small World (HNSW). Use these examples to understand how to create HNSW indexes for vector approximate similarity searches.

With Navigable Small World (NSW), the idea is to build a proximity graph where each vector in the graph connects to several others based on three characteristics:

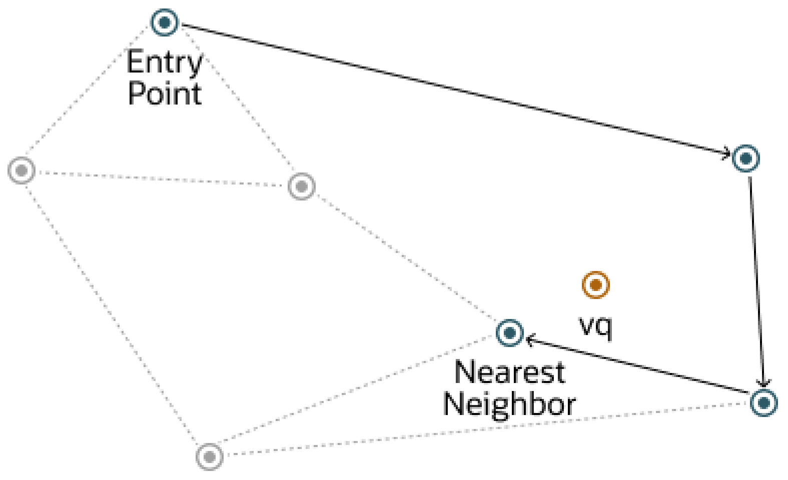
- The distance between vectors
- The maximum number of closest vector candidates considered at each step of the search during insertion (`EFCONSTRUCTION`)
- Within the maximum number of connections (`NEIGHBORS`) permitted per vector

If the combination of the above two thresholds is too high, then you may end up with a densely connected graph, which can slow down the search process. On the other hand, if the combination of those thresholds is too low, then the graph may become too sparse and/or disconnected, which makes it challenging to find a path between certain vectors during the search.

Navigable Small World (NSW) graph traversal for vector search begins with a predefined entry point in the graph, accessing a cluster of closely related vectors. The search algorithm employs two key lists: Candidates, a dynamically updated list of vectors that we encounter while traversing the graph, and Results, which contains the vectors closest to the query vector found thus far. As the search progresses, the algorithm navigates through the graph, continually refining the Candidates by exploring and evaluating vectors that might be closer than those in the Results. The process concludes once there are no vectors in the Candidates closer than the farthest in the Results, indicating a local minimum has been reached and the closest vectors to the query vector have been identified.

This is illustrated in the following graphic:

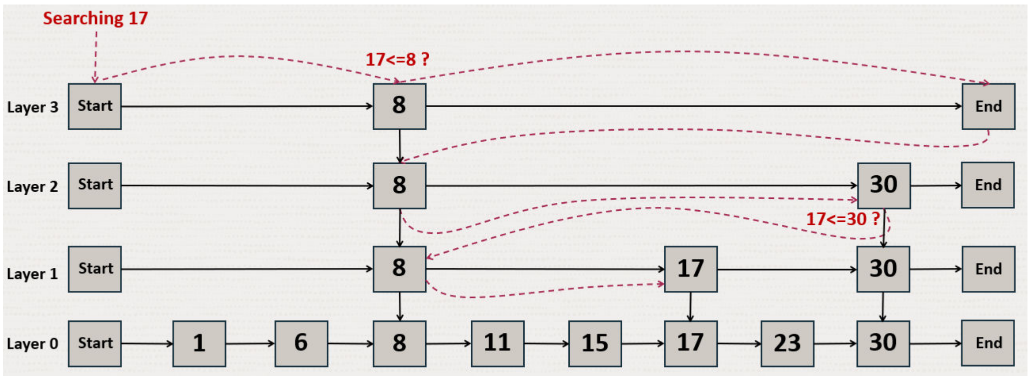
Figure 5-2   Navigable Small World Graph



The described method demonstrates robust performance up to a certain scale of vector insertion into the graph. Beyond this threshold, the Hierarchical Navigable Small World (HNSW) approach enhances the NSW model by introducing a multi-layered hierarchy, akin to the structure observed in Probabilistic Skip Lists. This hierarchical architecture is implemented by distributing the graph's connections across several layers, organizing them in a manner where each subsequent layer contains a subset of the links from the layer below. This stratification ensures that the top layers capture long-distance links, effectively serving as express pathways across the graph, while the lower layers focus on shorter links, facilitating fine-grained, local navigation. As a result, searches begin at the higher layers to quickly approximate the region of the target vector, progressively moving to lower layers for a more precise search, significantly improving search efficiency and accuracy by leveraging shorter links (smaller distances) between vectors as one moves from the top layer to the bottom.

To better understand how this works for HNSW, let's look at how this hierarchy is used for the Probability Skip List structure:

Figure 5-3 Probability Skip List Structure

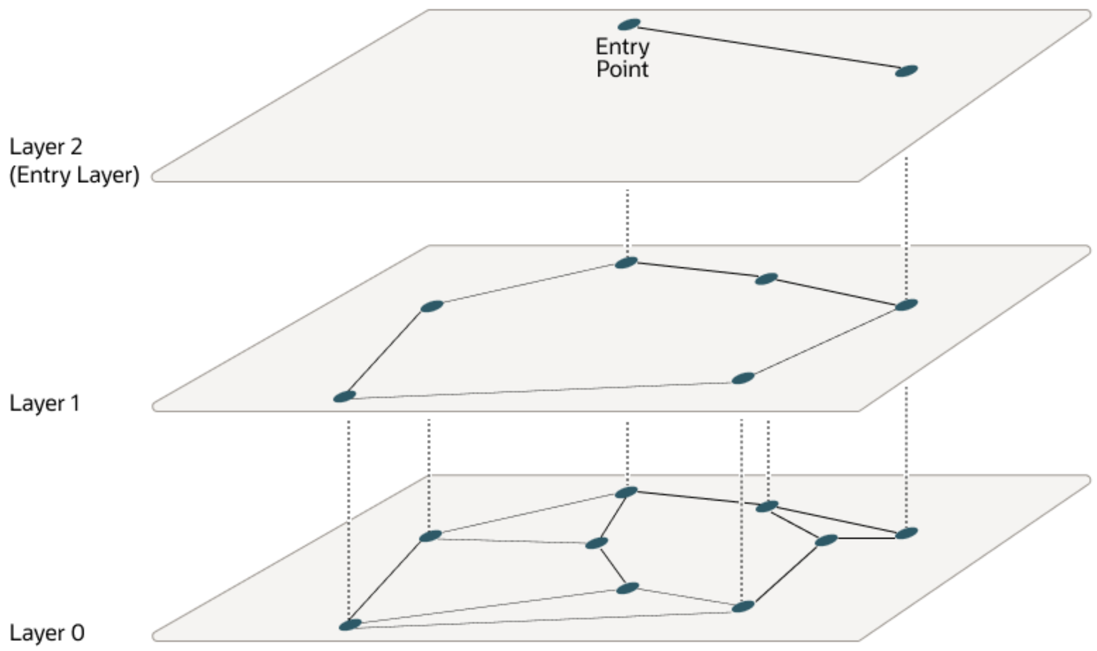


The Probability Skip List structure uses multiple layers of linked lists where the above layers are skipping more numbers than the lower ones. In this example, you are trying to search for number 17. You start with the top layer and jump to the next element until you either find 17, reach the end of the list, or you find a number that is greater than 17. When you reach the end of a list or you find a number greater than 17, then you start in the previous layer from the latest number less than 17.

HNSW uses the same principle with NSW layers where you find greater distances between vectors in the higher layers. This is illustrated by the following diagrams in a 2D space:

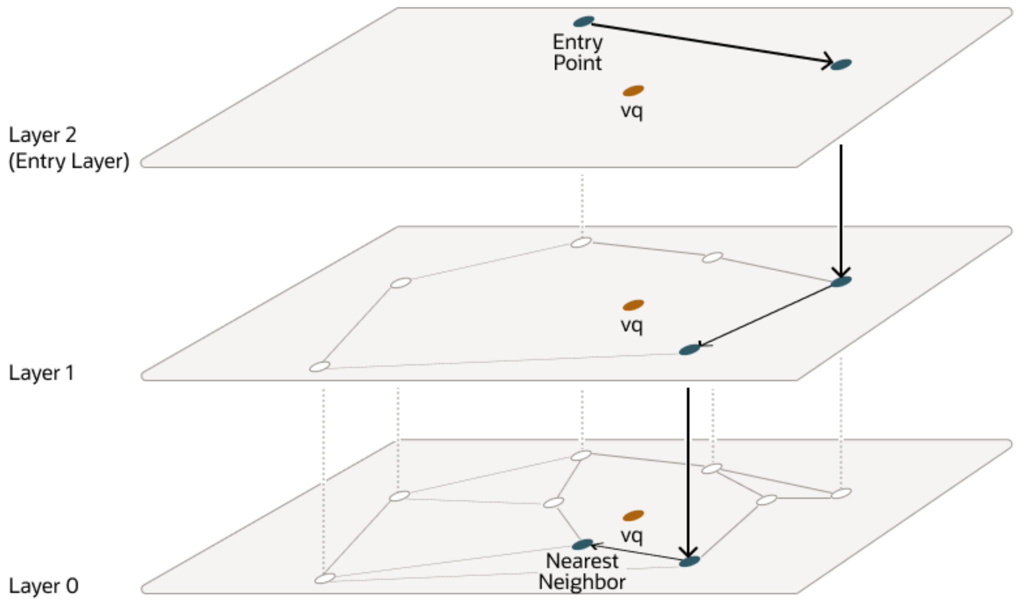
At the top layer are the longest edges and at the bottom layer are the shortest ones.

Figure 5-4   Hierarchical Navigable Small World Graphs



Starting from the top layer, the search in one layer starts at the entry vector. Then for each node, if there is a neighbor that is closer to the query vector than the current node, it jumps to that neighbor. The algorithm keeps doing this until it finds a local minimum for the query vector. When a local minimum is found in one layer, the search goes to the next layer by using the same vector in that new layer and the search continues in that layer. This process repeats itself until the local minimum of the bottom layer is found, which contains all the vectors. At this point, the search is transformed into an approximate similarity search using the NSW algorithm around that latest local minimum found to extract the top `k` most similar vectors to your query vector. While the upper layers can have a maximum of connections for each vector set by the `NEIGHBORS` parameter, layer `0` can have twice as much. This process is illustrated in the following graphic:

Figure 5-5   Hierarchical Navigable Small World Graphs Search



Layers are implemented using in-memory graphs (not Oracle Inmemory graph). Each layer uses a separate in-memory graph. As already seen, when creating an HNSW index, you can fine tune the maximum number of connections per vector in the upper layers using the `NEIGHBORS` parameter as well as the maximum number of closest vector candidates considered at each step of the search during insertion using the `EFCONSTRUCTION` parameter, where EF stands for Enter Factor.

As explained earlier, when using Oracle AI Vector Search to run an approximate search query using HNSW indexes, you have the possibility to specify a target accuracy at which the approximate search should be performed. In the case of an HNSW approximate search, you can specify a target accuracy percentage value to influence the number of candidates considered to probe the search. This is automatically calculated by the algorithm. A value of 100 will tend to impose a similar result as an exact search, although the system may still use the index and will not perform an exact search. The optimizer may choose to still use an index as it may be faster to do so given the predicates in the query. Instead of specifying a target accuracy percentage value, you can specify the `EFSEARCH` parameter to impose a certain maximum number of candidates to be considered while probing the index. The higher that number, the higher the accuracy.

Note:

- If you do not specify any target accuracy in your approximate search query, then you will inherit the one set when the index was created. You will see that at index creation, you can specify a target accuracy either using a percentage value or parameters values depending on the index type you are creating.
- It is possible to specify a different target accuracy at index search compared to the one set at index creation. For HNSW indexes, you may look at more neighbors using the `EFSEARCH` parameter (higher than the `EFCONSTRUCTION` value specified at index creation) to get more accurate results. The target accuracy that you give during index creation decides the index creation parameters and also acts as the default accuracy values for vector index searches.

Hierarchical Navigable Small World Index Syntax and Parameter

Syntax for Hierarchical Navigable Small World Index

Syntax

```
CREATE VECTOR INDEX vector_index_name
    ON table_name ( vector_column )
    [ GLOBAL ] ORGANIZATION INMEMORY NEIGHBOR GRAPH
    [ WITH ] [ DISTANCE metric name ]
    [ WITH TARGET ACCURACY percentage_value ]
    [ PARAMETERS ( TYPE
                    { HNSW , { NEIGHBORS max_closest_vectors_connected
                         |  M
max_closest_vectors_connected }
                    ,  EFCONSTRUCTION max_candidates_to_consider
                 |
                 IVF , { NEIGHBOR PARTITIONS number_of_partitions
                              | SAMPLE_PER_PARTITION number_of_samples
                              | MIN_VECTORS_PER_PARTITION
min_number_of_vectors_per_partition }
               }
     ]
      [ PARALLEL degree_of_parallelism ]
```

For detailed information, see CREATE VECTOR INDEX in *Oracle Database SQL Language Reference*

Neighbor Partition Vector Index

Inverted File Flat (IVF) index is the only type of Neighbor Partition vector index supported. Inverted File Flat Index (IVF Flat or simply IVF) is a partitioned-based index which balance high search quality with reasonable speed.

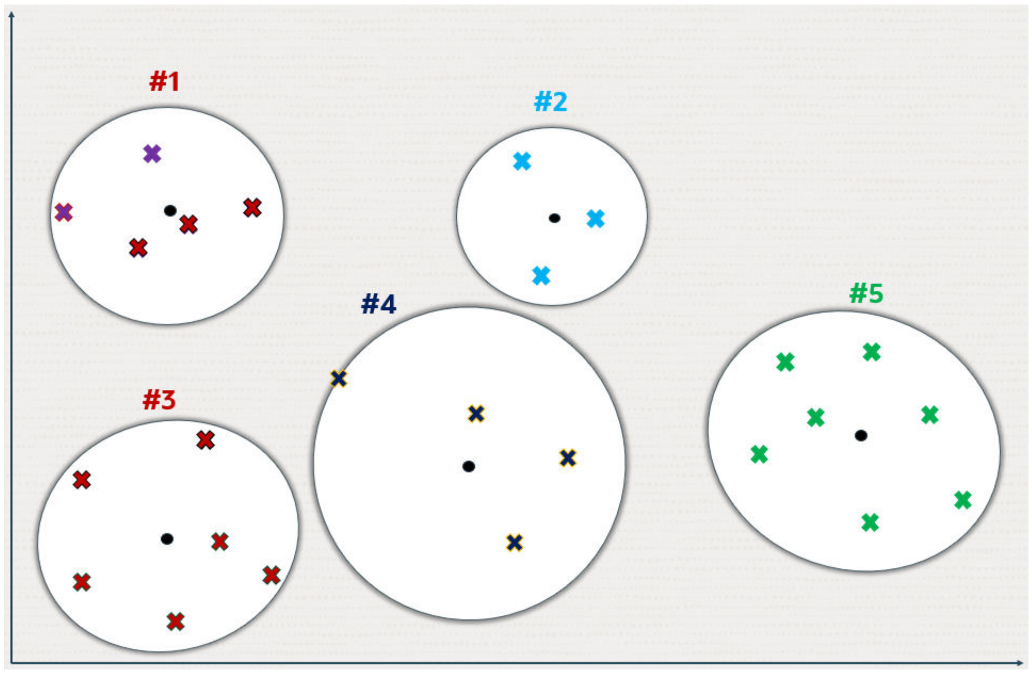
- Understand Inverted File Flat Vector Indexes
  The default type of index created for a Neighbor Partition vector index is Inverted File Flat (IVF) vector index. The IVF index is a technique designed to enhance search efficiency by narrowing the search area through the use of neighbor partitions or clusters.
- Inverted File Flat Index Syntax and Parameter
  Syntax for Inverted File Flat Index

Understand Inverted File Flat Vector Indexes

The default type of index created for a Neighbor Partition vector index is Inverted File Flat (IVF) vector index. The IVF index is a technique designed to enhance search efficiency by narrowing the search area through the use of neighbor partitions or clusters.

The following diagrams depict how partitions or clusters are created in an approximate search done using a 2D space representation. But this can be generalized to much higher dimensional spaces.

Figure 5-6 Inverted File Flat Index Using 2D



Crosses represent the vector data points in this space.

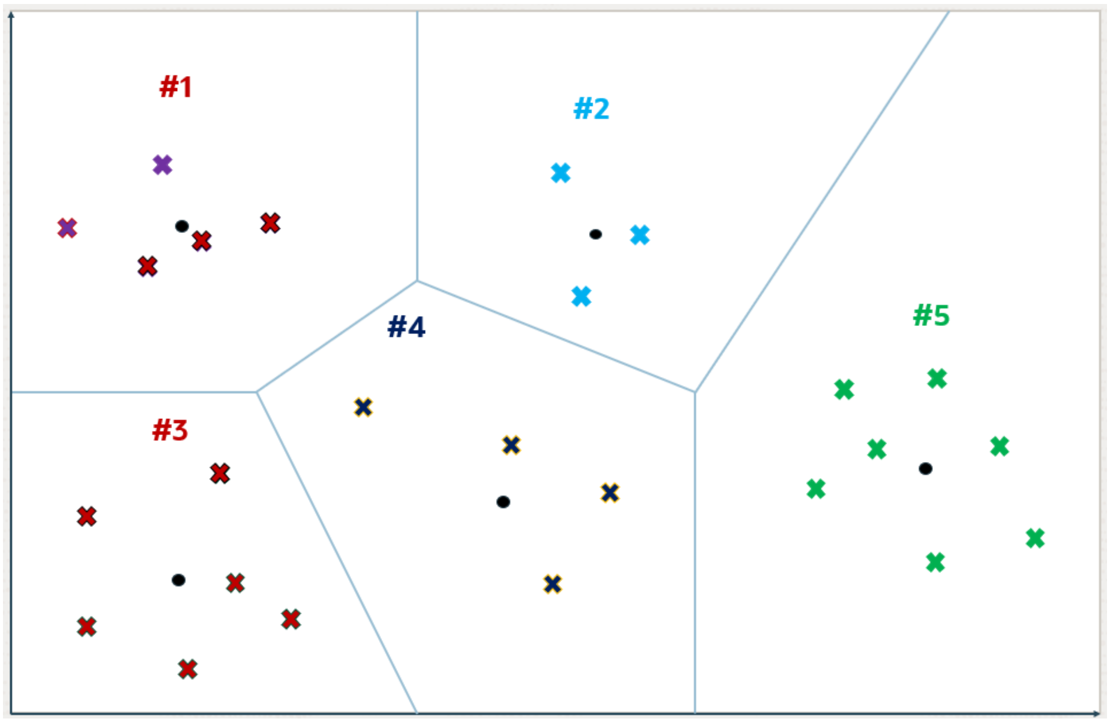
New data points, shown as small plain circles, are added to identify `k` partition centroids, where the number of centroids (`k`) is determined by the size of the dataset (`n`). Typically `k` is set to the square root of `n`, though it can be adjusted by specifying the `NEIGHBOR PARTITIONS` parameter during index creation.

Each centroid represents the average vector (center of gravity) of the corresponding partition.

The centroids are calculated by a training pass over the vectors whose goal is to minimize the total distance of each vector from the closest centroid.

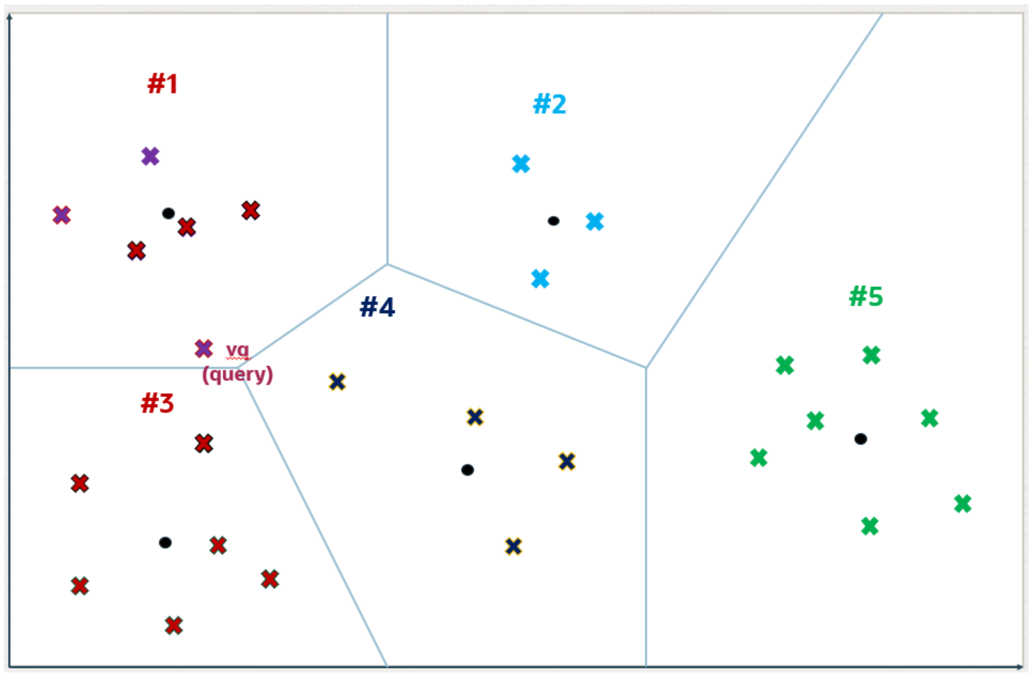
The centroids ends up partitioning the vector space into `k` partitions. This division is conceptually illustrated as expanding circles from the centroids that stop growing as they meet, forming distinct partitions.

Figure 5-7   Inverted File Flat Index



Except for those on the periphery, each vector falls within a specific partition associated with a centroid.

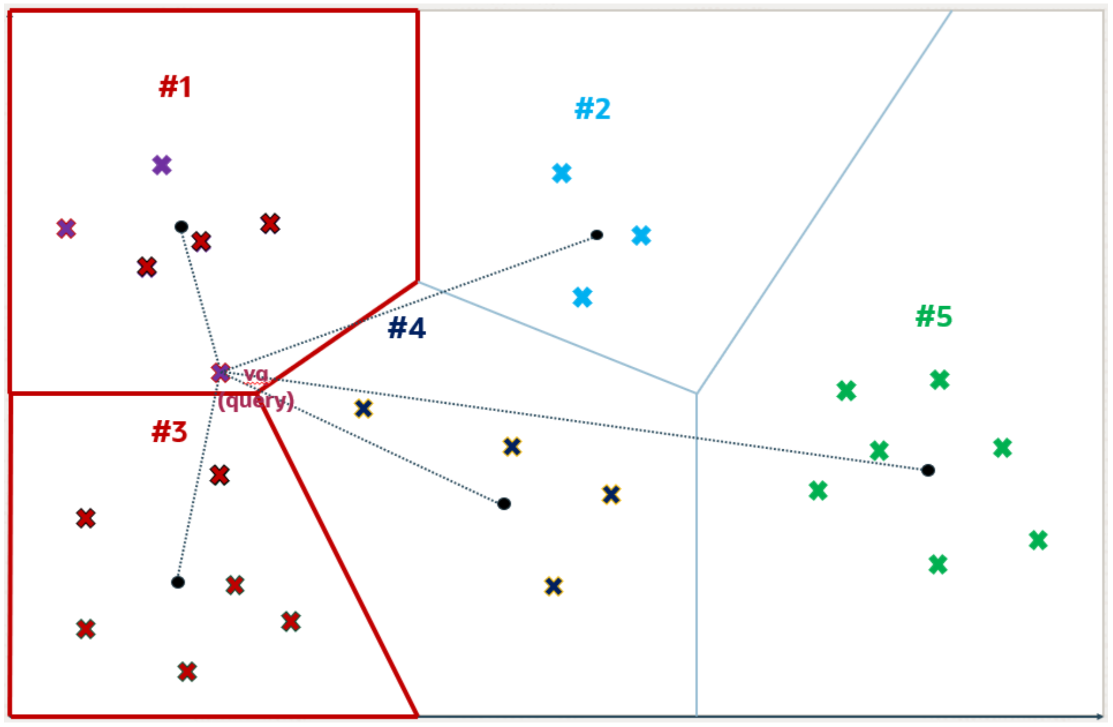
Figure 5-8 Inverted File Flat Index



For a query vector `vq`, the search algorithm identifies the nearest `i` centroids, where `i` defaults to the square root of `k` but can be adjusted for a specific query by setting the `NEIGHBOR PARTITION PROBES` parameter. This adjustment allows for a trade-off between search speed and accuracy.

Higher numbers for this parameter will result in higher accuracy. In this example, `i` is set to 2 and the two identified partitions are partitions number 1 and 3.

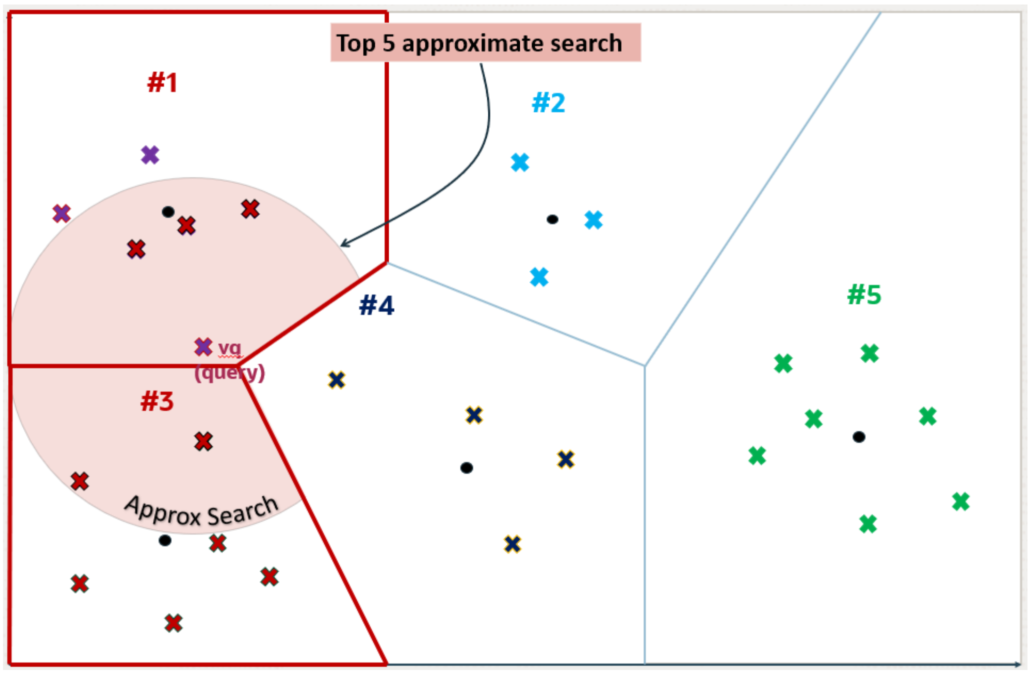
Figure 5-9 Inverted File Flat Index



Once the `i` partitions are determined, they are fully scanned to identify, in this example, the top 5 nearest vectors. This number 5 can be different from `k` and you specify this number in your query. The five nearest vectors to `vq` found in partitions number 1 and 3 are highlighted in the following diagram.

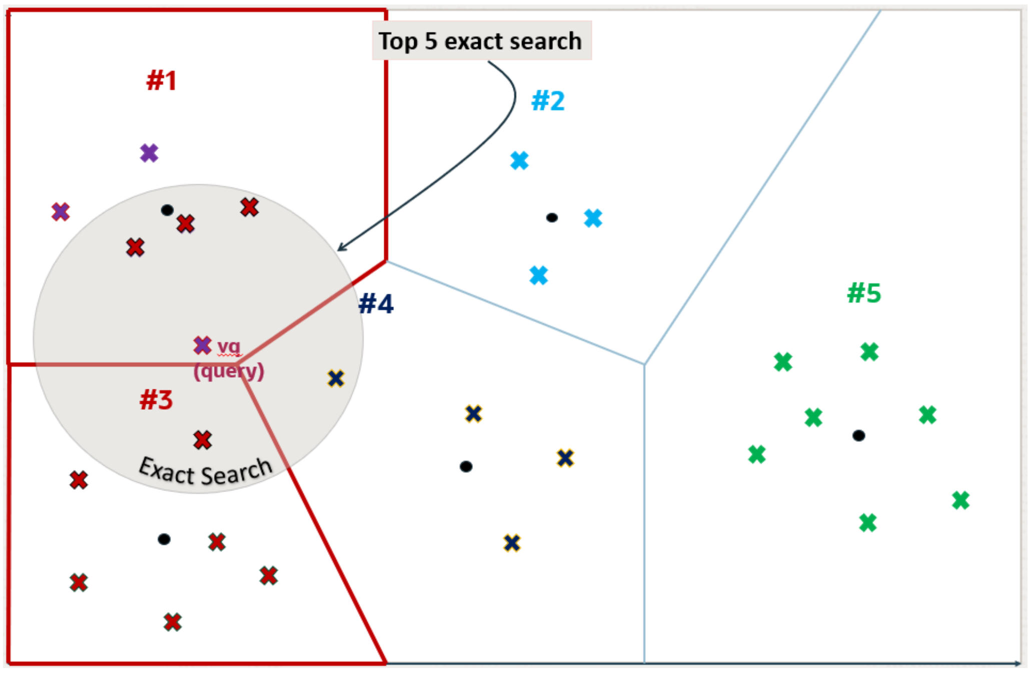
This method constitutes an approximate search as it limits the search to a subset of partitions, thereby accelerating the process but potentially missing closer vectors in unexamined partitions. This example illustrates that an approximate search might not yield the exact nearest vectors to `vq`, demonstrating the inherent trade-off between search efficiency and accuracy.

Figure 5-10 Inverted File Flat Index



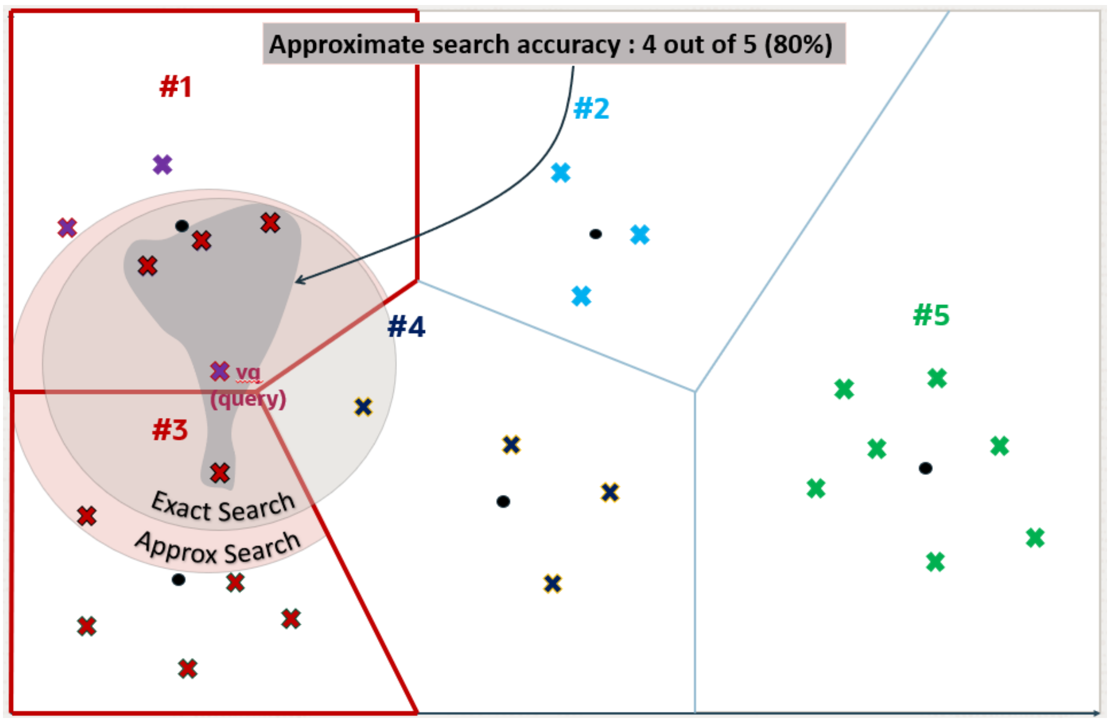
However, the five exact nearest vectors from `vq` are not the ones found by the approximate search. You can see that one of the vectors in partition number 4 is closer to `vq` than one of the retrieved vectors in partition number 3.

Figure 5-11 Inverted File Flat Index



You can now see why using vector index searches is not always an exact search and is called an approximate search instead. In this example, the approximate search accuracy is only 80% as it has retrieved only 4 out of 5 of the exact search vectors' result.

Figure 5-12   Inverted File Flat Index



When using Oracle AI Vector Search to run an approximate search query using vector indexes, you have the possibility to specify a target accuracy at which the approximate search should be performed. In the case of an IVF approximate search, you can specify a target accuracy percentage value to influence the number of partitions used to probe the search. This is automatically calculated by the algorithm. A value of 100 will tend to impose an exact search, although the system may still use the index and will not perform an exact search. The optimizer may choose to still use an index as it may be faster to do so given the predicates in the query. Instead of specifying a target accuracy percentage value, you can specify the `NEIGHBOR PARTITION PROBES` parameter to impose a certain maximum number of partitions to be probed by the search. The higher that number, the higher the accuracy.

Note:

- If you do not specify any target accuracy in your approximate search query, then you will inherit the one set when the index was created. You will see that at index creation time, you can specify a target accuracy either using a percentage value or parameters values depending on the type of index you are creating.
- It is possible to specify a different target accuracy at index search, compared to the one set at index creation. For IVF indexes, you may probe more centroid partitions using the `NEIGHBOR PARTITION PROBES` parameter to get more accurate results. The target accuracy that you provide during index creation decides the index creation parameters and also acts as the default accuracy value for vector index searches.

Inverted File Flat Index Syntax and Parameter

Syntax for Inverted File Flat Index

Syntax

```
CREATE VECTOR INDEX <vector index name>
ON <table name> ( <vector column> )
[GLOBAL] ORGANIZATION NEIGHBOR PARTITIONS
[WITH] [DISTANCE <metric name>]
[WITH TARGET ACCURACY <percentage value>
[PARAMETERS ( TYPE IVF, { NEIGHBOR PARTITIONS <number of partitions> |
SAMPLE_PER_PARTITION
    <number of samples> | MIN_VECTORS_PER_PARTITION <minimum number of
vectors per partition>
})]]
[PARALLEL <degree of parallelism>];
```

Parameter

`NEIGHBOR PARTITIONS` determines the target number of centroid partitions that are created by the index.

`SAMPLE_PER_PARTITION` decides the total number of vectors that are passed to the clustering algorithm (samples_per_partition * neighbor_partitions). Passing all the vectors could significantly increase the total index creation time. The goal is to pass in a subset of vectors that can capture the data distribution.

`MIN_VECTORS_PER_PARTITION` represents the target minimum number of vectors per partition. The goal is to trim out any partition that can end up with few vectors (<= 100).

The valid range for IVF vector index parameters are:

- `ACCURACY`: > 0 and <= 100
- `DISTANCE`: EUCLIDEAN, L2_SQUARED (aka EUCLIDEAN_SQUARED), COSINE, DOT, MANHATTAN, HAMMING

- `TYPE`: IVF
- `NEIGHBOR PARTITIONS`: >0 and <= 10000000
- `SAMPLE_PER_PARTITION`: from 1 to (num_vectors/neighbor_partitions)
- `MIN_VECTORS_PER_PARTITION`: from 0 (no trimming of centroid partitions) to total number of vectors (would result in 1 centroid partition)

Examples

```
CREATE VECTOR INDEX galaxies_ivf_idx ON galaxies (embedding) ORGANIZATION
NEIGHBOR PARTITIONS
DISTANCE COSINE
WITH TARGET ACCURACY 95;

CREATE VECTOR INDEX galaxies_ivf_idx ON galaxies (embedding) ORGANIZATION
NEIGHBOR PARTITIONS
DISTANCE COSINE
WITH TARGET ACCURACY 90 PARAMETERS (type IVF, neighbor partitions 10);
```

Guidelines for Using Vector Indexes

Use these guidelines to create and use Hierarchical Navigable Small World (HNSW) or Inverted File Flat (IVF) vector indexes.

Create Index Guidelines

The minimum information required to create a vector index is to specify one VECTOR data type table column and a vector index type: `INMEMORY NEIGHBOR GRAPH` for HNSW and `NEIGHBOR PARTITIONS` for IVF. However, you also have the possibility to specify more information, such as the following:

- You can optionally provide more information including the distance metric to use. Supported metrics are `EUCLIDEAN SQUARED`, `EUCLIDEAN`, `COSINE`, `DOT`, `MANHATTAN`, and `HAMMING`. If not specified, `COSINE` is used by default.
- Specific parameters that impact the accuracy of index creation and approximate searches. A target accuracy percentage value and, `NEIGHBORS` (or M) and `EFCONSTRUCTION` for HNSW and `NEIGHBOR PARTITIONS` for IVF.
- You can create globally partitioned vector indexes.
- You can also specify the degree of parallelism to use for index creation.

You cannot currently define a VECTOR index on:

- External tables
- IOTs
- Clusters/Cluster tables
- Global Temp tables
- Blockchain tables
- Materialized views
- Non-vector columns (`VARCHAR`, `NUMBER`, and so on.)

- Function-based vector index
- Sharded tables

You can find information about your vector indexes by looking at `ALL_INDEXES`, `DBA_INDEXES`, and `USER_INDEXES` family of views. The columns of interest are `INDEX_TYPE` (`VECTOR`) and `INDEX_SUBTYPE` (`INMEMORY_NEIGHBOR_GRAPH_HNSW` or `NEIGHBOR_PARTITIONS_IVF`). In the case the index is not a vector index, `INDEX_SUBTYPE` is `NULL`.

See VECSYS.VECTOR$INDEX for detailed information about vector indexes.

Note:

- The `VECTOR` column is designed to be extremely flexible to support vectors of any number of dimensions and any format for the vector dimensions. However, you can create a vector index only on a `VECTOR` column containing vectors that all have the same number of dimensions. This is required as you can't compute distances over vectors with different dimensions. For example, if a `VECTOR` column is defined as `VECTOR(*, FLOAT32)`, and two vectors with different dimensions (128 and 256 respectively) are inserted in that column. When you try to create the vector index on that column, you will get an error.
- You can only create one type of vector index per vector column.
- Oracle recommends that you allocate larger, temporary tablespaces for proper Inverted File Flat (IVF) vector index creation with big vector spaces and vector sizes. In such cases, the system internally makes extensive use of temporary space.
- If you are running your Oracle Database on a RAC environment, you cannot create HNSW indexes. On a non-RAC single instance environment, you can create both HNSW and IVF indexes. Using HNSW is the preferred type if it fits entirely into memory.
- On a RAC environment you can set up a vector pool on each instance for the best performance of IVF indexes.

Use Index Guidelines

For the Oracle Database Optimizer to consider a vector index, you must ensure to verify these conditions in your SQL statements:

- The similarity search SQL query must include the `APPROX` or `APPROXIMATE` keyword.
- The vector index must exist.
- The distance function for the index must be the same as the distance function used in the `vector_distance()` function.
- If the vector index DDL does not specify the distance function and the `vector_distance()` function uses `COSINE`, `DOT`, `MANHATTAN` or `HAMMING`, then the vector index is not used.

- If the vector index DDL uses the `DOT` distance function and the `vector_distance()` function uses the default distance function `[COSINE]`, then the vector index is not used.
- The `vector_distance()` must not be encased in another SQL function.
- If using the partition row-limiting clause, then the vector index is not used.
- Index accuracy with an IVF index may diminish over time due to DML operations being performed on the underlying table. You can check for this by using the `INDEX_ACCURACY_QUERY` function provided by the `DBMS_VECTOR` package. In such a case, the index can be rebuild using the `REBUILD_INDEX` function also provided by the `DBMS_VECTOR` package. See *Oracle Database PL/SQL Packages and Types Reference* for more information about `DBMS_VECTOR` and its subprograms.
- After an HNSW vector index is created, DML operations are not permitted on the indexed table. DML operations are supported when using IVF indexes.

Note:

When the database instance is restarted, the existing HNSW indexes must be rebuilt as these structures are inmemory-only structures. There are three options for you to recreate an HNSW vector index after a restart:

- Manually drop the index and create it again. This requires you to remember and provide the original index creation parameters.
- `DBMS_VECTOR.REBUILD_INDEX`: This procedure uses the `DBMS_METADATA.GET_DDL` function to get all of the index creation parameters. You may override the parameters by passing their values into the procedure. For more information about the `DBMS_VECTOR.REBUILD` procedure, see *Oracle Database PL/SQL Packages and Types Reference*.
- Automatic reload: The `VECTOR_INDEX_NEIGHBOR_GRAPH_RELOAD` initialization parameter is set to `OFF` by default. If set to `RESTART`, the system automatically loads the HNSW indexes one by one through a background task. It will use the same parallelism and the index creation parameters that you had specified during the original HNSW index creation.

Note:

Except for `ALTER TABLE tab SUBPARTITION`/`PARTITION` (`RANGE`/`LIST`) with or without Update Global Indexes, global vector indexes are marked as unusable as part of other Partition Management Operations on a partitioned table. In those cases you must manually rebuild the global vector indexes.

Index Accuracy Report

The index accuracy reporting feature lets you determine the accuracy of your vector indexes.

Accuracy of One Specific Query Vector

After a vector index is created, you may be interested to know how accurate your vector searches are. One possibility might be to run two queries using the same query vector, that is, one performing an approximate search using a vector index and the other performing an exact search without an index. Then, you need to manually compare the results to determine the real accuracy of your index.

Instead, you can use an index accuracy report provided by the `DBMS_VECTOR.INDEX_ACCURACY_QUERY` procedure. This procedure provides an accuracy report for a top-K index search for a specific query vector and a specific target accuracy.

Here is a usage example of this procedure using our galaxies scenario:

```
declare
    q_v VECTOR;
    report varchar2(128);
begin
    q_v := to_vector('[0,1,1,0,0]');
    report := dbms_vector.index_accuracy_query(
        OWNER_NAME => 'COSMOS',
        INDEX_NAME => 'GALAXIES_HNSW_IDX',
        qv => q_v, top_K =>10,
        target_accuracy =>90 );
    dbms_output.put_line(report);
end;
/
```

The preceding example computes the top-10 accuracy of the `GALAXIES_HNSW_IDX` vector index using the embedding corresponding to the NGC 1073 galaxy and a 90% accuracy requested.

The index accuracy report for this may look like:

```
Accuracy achieved (100%) is 10% higher than the Target Accuracy
requested (90%)
```

The possible parameters are:

- `owner_name`: Index owner name
- `index_name`: Index name
- `qv`: Query vector
- `top_K`: Top K value for accuracy computation
- `target_accuracy`: Target accuracy for the index

Accuracy of Automatically Captured Query Vectors

An overloaded version of the `DBMS_VECTOR.INDEX_ACCURACY_REPORT` function allows you to capture from your past workloads, accuracy values achieved by your approximate searches using a particular vector index for a certain period of time. Query vectors used for approximate searches are captured automatically in memory and persisted to a catalog table every hour.

The `INDEX_ACCURACY_REPORT` function computes the achieved accuracy using the captured query vectors for a given index. To compute the achieved accuracy for each query vector, the function compares the result set of approximate similarity searches with exact similarity searches for the same query vectors.

The accuracy findings are stored in dictionary and exposed using the `DBA_VECTOR_INDEX_ACCURACY_REPORT` dictionary view.

Here is a usage example of this function using the galaxies scenario:

```
VARIABLE t_id NUMBER;
BEGIN
  :t_id := DBMS_VECTOR.INDEX_ACCURACY_REPORT('VECTOR', 'GALAXIES_HNSW_IDX');
END;
/
```

You can also run the following statement to get the corresponding task identifier:

```
SELECT DBMS_VECTOR.INDEX_ACCURACY_REPORT('VECTOR', 'GALAXIES_HNSW_IDX');
```

The following are possible parameters for the `INDEX_ACCURACY_REPORT` function:

- `owner_name` (IN): Index owner name
- `ind_name` (IN): Index name
- `start_time` (IN): Query vectors captured from this time are considered for the accuracy computation. A `NULL` `start_time` uses query vectors captured in the last 24 hours.
- `end_time` (IN): Query vectors captured until this time are considered for accuracy computation. A `NULL` `end_time` uses query vectors captured from `start_time` until the current time.
- Return Values: A numeric task ID if the accuracy for the given index was successfully computed. Otherwise, a `NULL` task ID is returned.

Note:

- If both `start_time` and `end_time` are `NULL`, accuracy is computed using query vectors captured in the last 24 hours.
- If `start_time` is `NULL` and `end_time` is not `NULL`, accuracy is computed using query vectors captured between 24 hours before `end_time` until `end_time`.
- If `start_time` is not `NULL` and `end_time` is `NULL`, accuracy is computed using query vectors captured between `start_time` and the current time.

You can see the analysis results using the `DBA_VECTOR_INDEX_ACCURACY_REPORT` view:

```
desc DBA_VECTOR_INDEX_ACCURACY_REPORT


 Name                                      Null?    Type
 ----------------------------------------- --------
----------------------------
 TASK_ID                                            NUMBER
 TASK_TIME                                             TIMESTAMP(6)
 OWNER_NAME                                            VARCHAR2(128)
 INDEX_NAME                                            VARCHAR2(128)
 INDEX_TYPE                                            VARCHAR2(16)
 MIN_TARGET_ACCURACY                                   NUMBER
 MAX_TARGET_ACCURACY                                   NUMBER
 NUM_VECTORS                                           NUMBER
 MEDIAN_ACHIEVED_ACCURACY                              NUMBER
 MIN_ACHIEVED_ACCURACY                                 NUMBER
 MAX_ACHIEVED_ACCURACY                                 NUMBER
```

Select target accuracy values in the following statement:

```
SELECT MIN_TARGET_ACCURACY, MAX_TARGET_ACCURACY, num_vectors,
MIN_ACHIEVED_ACCURACY, MEDIAN_ACHIEVED_ACCURACY, MAX_ACHIEVED_ACCURACY
FROM DBA_VECTOR_INDEX_ACCURACY_REPORT WHERE task_id = 1;



MIN_TARGET_ACCURACY MAX_TARGET_ACCURACY NUM_VECTORS
MIN_ACHIEVED_ACCURACY MEDIAN_ACHIEVED_ACCURACY MAX_ACHIEVED_ACCURACY
------------------- ------------------- -----------
--------------------- ------------------------ ---------------------
                  1                  10           2
49                     57                      65
                 11                  20           3
60                     73                      83
                 21                  30           3
44                     64                      84
                 31                  40           2
63                   76.5                      90
                 41                  50           3
63                     81                      90
                 61                  70           2
57                     68                      79
                 71                  80           3
79                     87                      89
                 81                  90           3
70                     71                      78
                 91                 100           4
67                   79.5                      88
```

Each row in the output represents a bucket of 10 target accuracy values: 1-10, 11-20, 21-30, … , 91-100.

Consider the following partial statement that runs an approximate similarity search for a particular query vector and a particular target accuracy:

```
SELECT ...
FROM ...
WHERE ...
ORDER BY VECTOR_DISTANCE( embedding, :my_query_vector, COSINE )
FETCH APPROXIMATE FIRST 3 ROWS ONLY WITH TARGET ACCURACY 65;
```

Once the preceding approximate similarity search is run and captured by your accuracy report task, the value of NUM_VECTORS would be increased by one in row 6 (bucket values between 61 and 70) of the results of the select statement on the DBA_VECTOR_INDEX_ACCURACY_REPORT view for your task. NUM_VECTORS represents the number of query vectors that fall in a particular target accuracy bucket.

MIN_ACHIEVED_ACCURACY, MEDIAN_ACHIEVED_ACCURACY, and MAX_ACHIEVED_ACCURACY are the actual achieved accuracy values for the given target accuracy bucket.

Note:

The initialization parameter VECTOR_QUERY_CAPTURE is used to enable and disable capture of query vectors. The parameter value is set to ON by default. You can turn off this background functionality by setting VECTOR_QUERY_CAPTURE to OFF. When VECTOR_QUERY_CAPTURE is ON, the database captures some of the query vectors through sampling. The captured query vectors are retrained for a week and then purged automatically.

6 Use SQL Functions for Vector Operations

There are a number of SQL functions and operators that you can use with vectors in Oracle AI Vector Search.

- Vector Distance Functions
  A vector distance function takes in two vector operands and a distance metric to compute a mathematical distance between those two vectors based on the distance metric provided. Distances determine similarity or dissimilarity between vectors.
- Other Basic Vector Functions
  Other basic vector operations for Oracle AI Vector Search involve creating, converting, and describing vectors.
- Oracle AI Vector Search SQL Functions
  Oracle AI Vector utilities provide the `VECTOR_CHUNKS` and `VECTOR_EMBEDDING` SQL functions for chunking and embedding data, respectively.

Vector Distance Functions

A vector distance function takes in two vector operands and a distance metric to compute a mathematical distance between those two vectors based on the distance metric provided. Distances determine similarity or dissimilarity between vectors.

- Vector Distance Metrics
  Measuring distances in a vector space is at the heart of identifying the most relevant results for a given query vector. That process is very different from the well-known keyword filtering in the relational database world.
- Vector Distance Operand to the VECTOR_DISTANCE Function
  `VECTOR_DISTANCE()` is the main function that allows you to calculate distances between two vectors.
- Shorthand Operators for Distances
  Oracle AI Vector Search provides shorthand operators that you can use for distance functions.

Vector Distance Metrics

Measuring distances in a vector space is at the heart of identifying the most relevant results for a given query vector. That process is very different from the well-known keyword filtering in the relational database world.

When working with vectors, there are several ways you can calculate distances to determine how similar, or dissimilar, two vectors are. Each distance metric is computed using different mathematical formulas. The time it takes to calculate those distances grows with the number of vector dimensions, which can go into thousands of dimensions. Generally it's best to match the distance metric you use to the one that was used to train your vector embedding model.

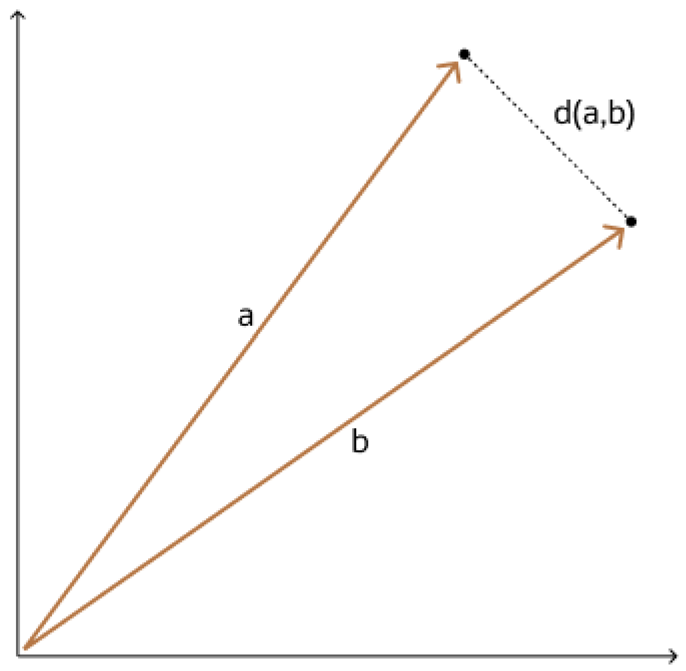
- Euclidean and Euclidean Squared Distances
  Euclidean distance reflects the distance between each of the vectors' coordinates being compared—basically the straight-line distance between two vectors. This is calculated using the Pythagorean theorem applied to the vector's coordinates `(SQRT(SUM((xi-yi)`^{2}`)))`.
- Cosine Similarity
  One of the most widely used similarity metric, especially in natural language processing (NLP), is cosine similarity, which measures the cosine of the angle between two vectors.
- Dot Product Similarity
  The dot product similarity of two vectors can be viewed as multiplying the size of each vector by the cosine of their angle. The corresponding geometrical interpretation of this definition is equivalent to multiplying the size of one of the vectors by the size of the projection of the second vector onto the first one, or vice versa.
- Manhattan Distance
  This metric is calculated by summing the distance between the dimensions of the two vectors that you want to compare.
- Hamming Similarity
  The Hamming distance between two vectors represents the number of dimensions where they differ.

Euclidean and Euclidean Squared Distances

Euclidean distance reflects the distance between each of the vectors' coordinates being compared—basically the straight-line distance between two vectors. This is calculated using the Pythagorean theorem applied to the vector's coordinates `(SQRT(SUM((xi-yi)`^{2}`)))`.

This metric is sensitive to both the vector's size and it's direction.

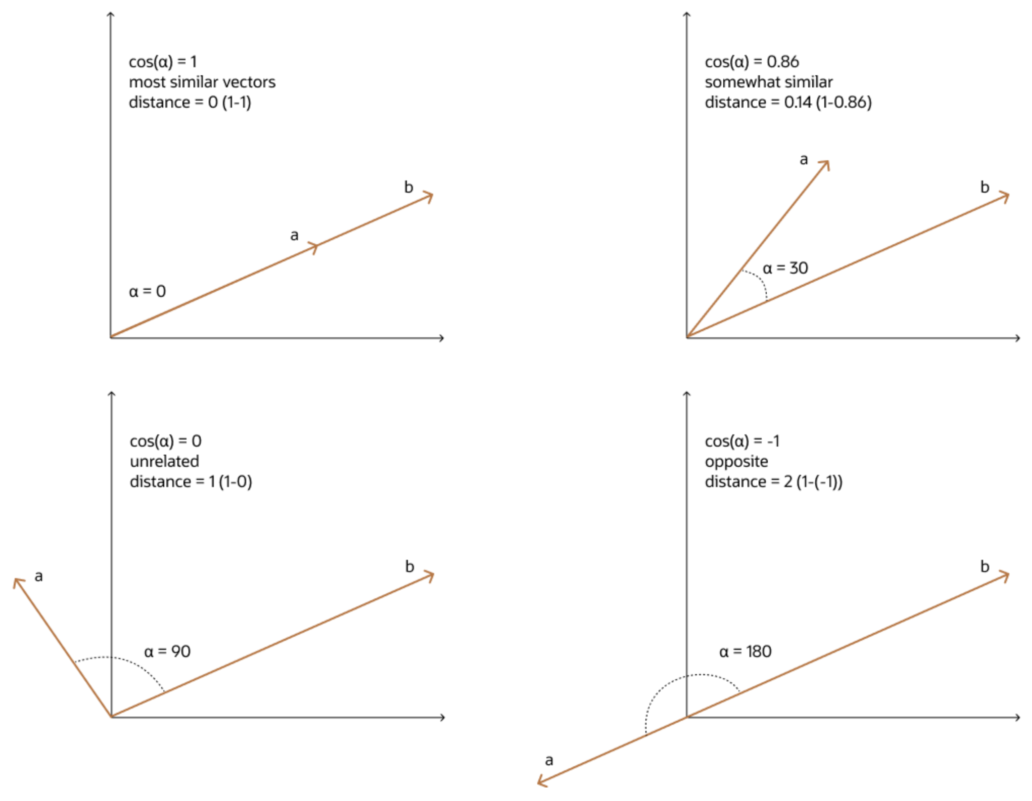
With Euclidean distances, comparing squared distances is equivalent to comparing distances. So, when ordering is more important than the distance values themselves, the Squared Euclidean distance is very useful as it is faster to calculate than the Euclidean distance (avoiding the square-root calculation).



Cosine Similarity

One of the most widely used similarity metric, especially in natural language processing (NLP), is cosine similarity, which measures the cosine of the angle between two vectors.

The smaller the angle, the more similar are the two vectors. Cosine similarity measures the similarity in the direction or angle of the vectors, ignoring differences in their size (also called *magnitude*). The smaller the angle, the bigger is its cosine. So the cosine distance and the cosine similarity have an inverse relationship. While cosine distance measures how different two vectors are, cosine similarity measures how similar two vectors are.



Dot Product Similarity

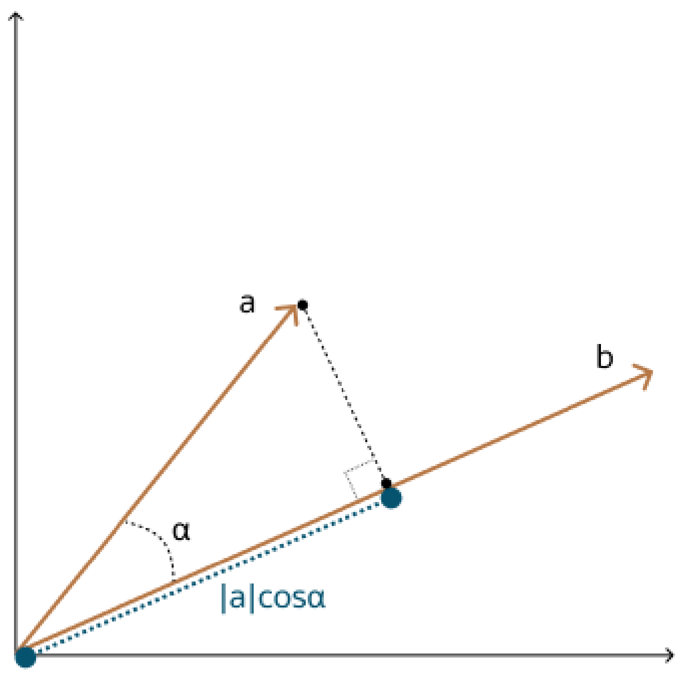
The dot product similarity of two vectors can be viewed as multiplying the size of each vector by the cosine of their angle. The corresponding geometrical interpretation of this definition is equivalent to multiplying the size of one of the vectors by the size of the projection of the second vector onto the first one, or vice versa.

As illustrated in the following diagram, you project one vector on the other and multiply the resulting vector sizes.

Incidentally, this is equivalent to the sum of the products of each vector's coordinate. Often, you do not have access to the cosine of the two vector's angle, hence this calculation is easier.

Larger dot product values imply that the vectors are more similar, while smaller values imply that they are less similar. Compared to using Euclidean distance, using the dot product similarity is especially useful for high-dimensional vectors.

Note that normalizing vectors and using the dot product similarity is equivalent to using cosine similarity. There are cases where dot product similarity is faster to evaluate than cosine similarity, and conversely where cosine similarity is faster than dot product similarity. A normalized vector is created by dividing each dimension by the norm (or length) of the vector, such that the norm of the normalized vector is equal to 1.

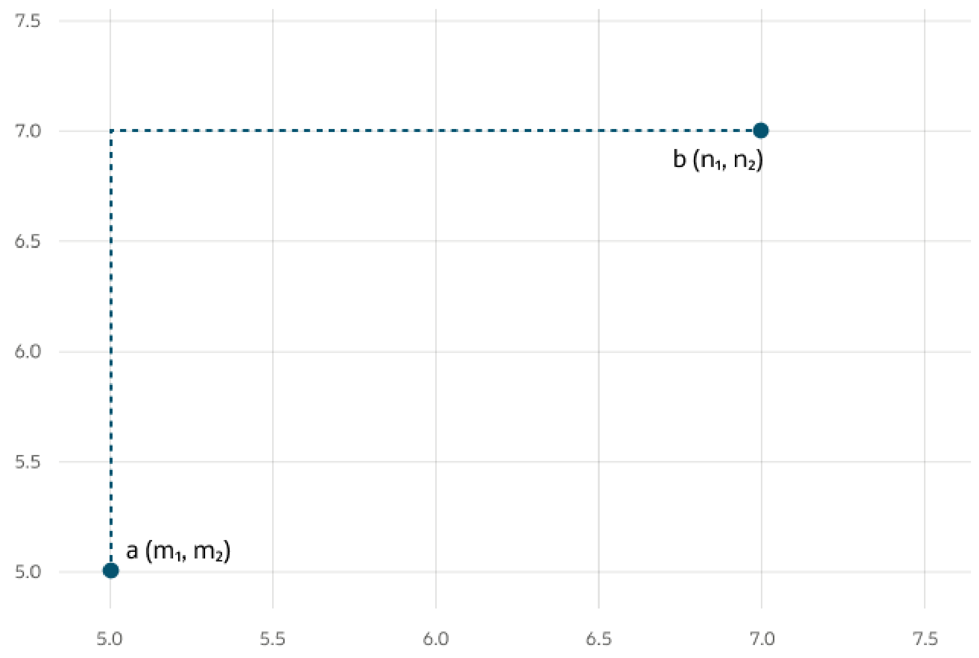


Manhattan Distance

This metric is calculated by summing the distance between the dimensions of the two vectors that you want to compare.

Imagine yourself in the streets of Manhattan trying to go from point A to point B. A straight line is not possible.

This metric is most useful for vectors describing objects on a uniform grid, such as city blocks, power grids, or a chessboard. It can be useful for higher dimensional vector spaces too. Compared to the Euclidean metric, the Manhattan metric is faster for calculations and you can use it advantageously for higher dimensional vector spaces.

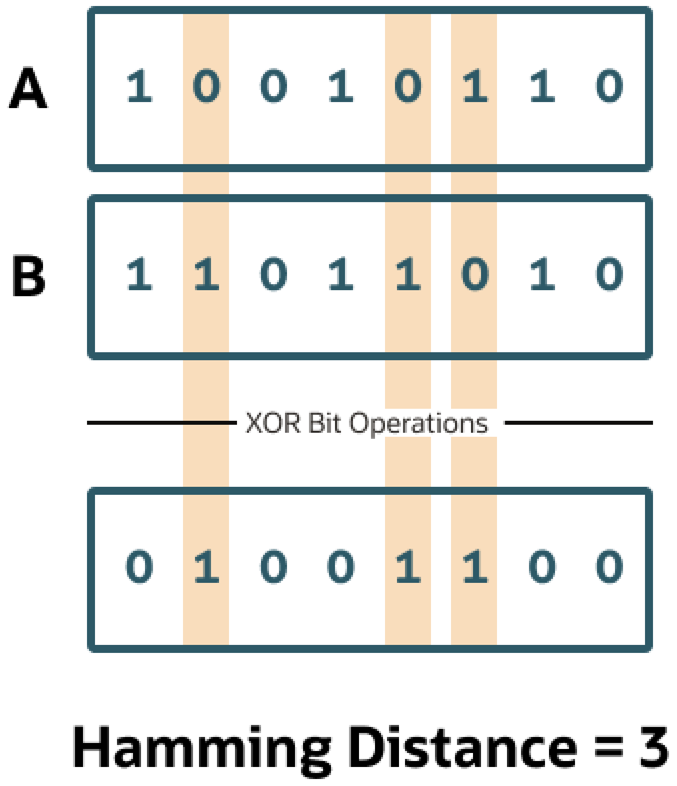


Hamming Similarity

The Hamming distance between two vectors represents the number of dimensions where they differ.

For example, when using binary vectors, the Hamming distance between two vectors is the number of bits you must change to change one vector into the other. To compute the Hamming distance between two vectors, you need to compare the position of each bit in the sequence. You can do this by using `exclusive or` (also called the XOR bit operation), which outputs 1 if the bits in the sequence do not match, and 0 otherwise. It's important to note that the bit strings need to be of equal length for the comparison to make sense.

The Hamming metric is mainly used with binary vectors for error detection over networks.



Vector Distance Operand to the VECTOR_DISTANCE Function

`VECTOR_DISTANCE()` is the main function that allows you to calculate distances between two vectors.

The `VECTOR_DISTANCE()` function takes two vectors as parameters. You can optionally specify a distance metric to calculate the distance desirably. If you do not specify a distance metric, then the default distance metric is the `COSINE` metric.

You can optionally use the following shorthand functions too : `L1_DISTANCE`, `L2_DISTANCE`, `COSINE_DISTANCE` and `INNER_PRODUCT`. These functions take two vectors as input and return the distance between them.

All of these functions return the vectors' distance as a `BINARY_DOUBLE`.

When using the `VECTOR_DISTANCE()` function to perform a similarity search, note the following caveats:

- If a similarity search query *does not* specify a distance metric in the `VECTOR_DISTANCE()` function, then the default `COSINE` metric will be used for both exact and approximate (index-based) searches.
- If a similarity search query does specify a distance metric in the `VECTOR_DISTANCE()` function, then an exact search with that distance metric is used if it conflicts with the distance metric specified in a vector index. If the two distance metrics are the same, then that will be used for both exact and approximate (index-based) searches.

Syntax

For detailed information on the vector functions, see Vector Functions in *Oracle SQL Language Reference*.

Related Topics

- Perform Exact Similarity Search
  A similarity search looks for the relative order of vectors compared to a query vector. Naturally, the comparison is done using a particular distance metric but what is important is the result set of your top closest vectors, not the distance between them.
- Perform Approximate Similarity Search Using Vector Indexes
  For a vector search to be useful, it needs to be fast and accurate. Approximate similarity searches seek a balance between these goals.

Shorthand Operators for Distances

Oracle AI Vector Search provides shorthand operators that you can use for distance functions.

Purpose

Oracle provides the following shorthand distance operators in lieu of their corresponding distance functions:

- `<->` is the **Euclidian distance operator**: `expr1 <-> expr2` is equivalent to `L2_DISTANCE(expr1, expr2)` or `VECTOR_DISTANCE(expr1, expr2, EUCLIDEAN)`
- `<=>` is the **cosine distance operator**: `expr1 <=> expr2` is equivalent to `COSINE_DISTANCE(expr1, expr2)` or `VECTOR_DISTANCE(expr1, expr2, COSINE)`
- `<#>` is the **negative dot product operator**: `expr1 <#> expr2` is equivalent to `-1*INNER_PRODUCT(expr1, expr2)` or `VECTOR_DISTANCE(expr1, expr2, DOT)`

Syntax

```
<expr1> <-> <expr2>
```

```
<expr1> <#> <expr2>
```

```
<expr1> <=> <expr2>
```

Parameters

`expr1` and *`expr2`* must evaluate to vectors and have the same number of dimensions. These operations return `NULL` if either *`expr1`* or *`expr2`* is `NULL`.

Example

- `'[1, 2]' <-> '[0,1]'`
- `v1 <-> '[' || '1,2,3' || ']'` is equivalent to `v1 <-> '[1, 2, 3]'`
- `v1 <-> '[1,2]'` is equivalent to `L2_DISTANCE(v1, '[1,2]')`
- `v1 <=> v2` is equivalent to `COSINE_DISTANCE(v1, v2)`
- `v1 <#> v2` is equivalent to `-1*INNER_PRODUCT(v1, v2)`

Other Basic Vector Functions

Other basic vector operations for Oracle AI Vector Search involve creating, converting, and describing vectors.

- Vector Constructors
  `TO_VECTOR()` and `VECTOR()` are synonymous constructors of vectors. The functions take a string of type `VARCHAR2` or `CLOB` as input and return a vector as output.
- Vector Serializers
  `FROM_VECTOR()` and `VECTOR_SERIALIZE()` are synonymous serializers of vectors.
- VECTOR_NORM
  The `VECTOR_NORM()` function returns the Euclidean norm of a vector `(SQRT(SUM((xi-yi)2)))` in the format of `BINARY_DOUBLE`.
- VECTOR_DIMENSION_COUNT
  The `VECTOR_DIMENSION_COUNT()` function returns the number of dimensions of a vector in the format of an Oracle number.
- VECTOR_DIMENSION_FORMAT
  The `VECTOR_DIMENSION_FORMAT()` returns the storage format of the vector. It returns a `VARCHAR2`, which can be one of the following values: `'INT8'`, `'FLOAT32'`, or `'FLOAT64'`.

Vector Constructors

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For detailed information, see the following in the *Oracle SQL Language Reference*:

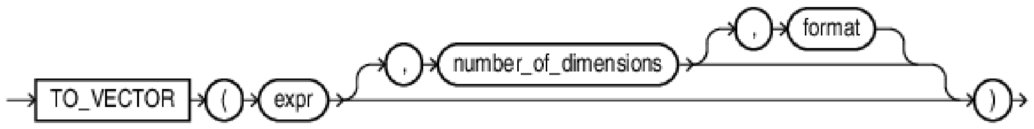
- TO_VECTOR
- VECTOR

- TO_VECTOR
- VECTOR
- Parameters
- Examples

TO_VECTOR

Syntax

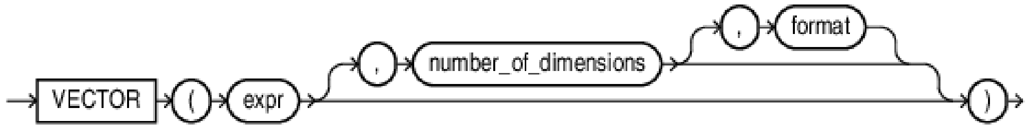
```
TO_VECTOR(expr [ , number_of_dimensions [ , format ] ] )
```



VECTOR

Syntax

```
VECTOR ( expr [ , number_of_dimensions [ , format ] ] )
```



Parameters

- *`expr`* must evaluate to either (a) a string that represents a vector (accepted input data types for the string are character types, JSON, `CLOB`, and `BLOB`) or (b) a vector. The valid string representation of a vector is in the form of an array of non-null numbers enclosed with a bracket and separated by commas, such as `'[1, 3.4, -05.60, 3e+4]'`. If it evaluates to a vector (the input's data type is `VECTOR`), the function serves the purpose of converting it to the specified or default format. The expression can be `NULL`, in which case the result is `NULL` as well. If a `BLOB` is used as the input parameter, it must represent the vector binary bytes.
- *`number_of_dimensions`* must be a numeric value that describes the number of dimensions of the vector to construct. The number of dimensions may also be specified as an asterisk `*`, in which case the dimension is determined by *`expr`*.
- *`format`* must be one of the following tokens: `INT8`, `FLOAT32`, `FLOAT64`, or `*`. This is the target internal storage format of the vector. If `*` is used, the format will be `FLOAT32`. Note that this behavior is a bit different than declaring a vector column. If you declare a column of type `VECTOR(3, *)`, then all inserted vectors will NOT have their storage format modified (stored as is).

Examples

```
SELECT TO_VECTOR('[34.6, 77.8]');
SELECT TO_VECTOR('[34.6, 77.8]', 2, FLOAT32);

SELECT TO_VECTOR('[34.6, 77.8]', 2, FLOAT32) FROM dual;

TO_VECTOR('[34.6,77.8]',2,FLOAT32)
---------------------------------------------------------
[3.45999985E+001,7.78000031E+001]
```

```
1 row selected.

SELECT TO_VECTOR('[34.6, 77.8, -89.34]', 3, FLOAT32);

TO_VECTOR('[34.6,77.8,-89.34]',3,FLOAT32)
------------------------------------------------------------
[3.45999985E+001,7.78000031E+001,-8.93399963E+001]

1 row selected.
```

Note:

- Applications using Oracle Client 23ai libraries or Thin mode drivers can insert vector data directly as a string or a `CLOB`. For example:

  ```
  INSERT INTO vecTab VALUES ('[1.1, 2.9, 3.14]');
  ```

- For applications using pre-Oracle Client 23ai libraries connected to Oracle Database 23ai, use the `TO_VECTOR()` SQL function to insert vector data. For example:

  ```
  INSERT INTO vecTab VALUES(TO_VECTOR('[1.1, 2.9, 3.14]'));
  ```

Vector Serializers

`FROM_VECTOR()` and `VECTOR_SERIALIZE()` are synonymous serializers of vectors.

Both functions take a vector as input and return a string of type `VARCHAR2` or `CLOB` as output. They optionally take a `RETURNING` clause to specify the returned data type. If `VARCHAR2` is specified without size, the returned value size is 32767. There is no support to convert to `CHAR`, `NCHAR`, and `NVARCHAR2`.

For detailed information, see the following in the *Oracle SQL Language Reference*:

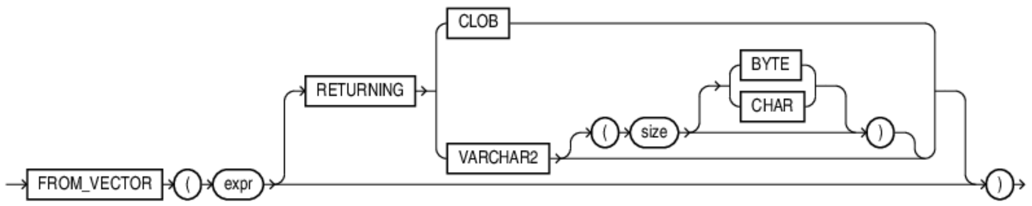
- FROM_VECTOR
- VECTOR_SERIALIZE

- FROM_VECTOR
- VECTOR_SERIALIZE
- Parameters
- Examples

FROM_VECTOR

Syntax

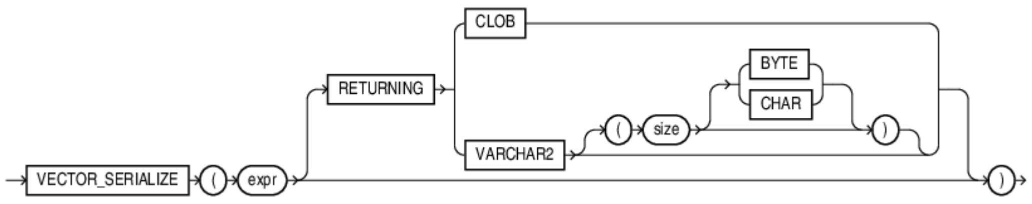
```
FROM_VECTOR ( expr [ RETURNING ( CLOB | VARCHAR2 [ ( size [BYTE |
CHAR] ) ] ) ] )
```



VECTOR_SERIALIZE

Syntax

```
VECTOR_SERIALIZE ( expr [ RETURNING ( CLOB | VARCHAR2 [ ( size [BYTE |
CHAR] ) ] ) ] )
```



Parameters

expr must have a vector type. The function returns `NULL` if *expr* is `NULL`.

Examples

```
SELECT FROM_VECTOR(TO_VECTOR('[1, 2, 3]') );

SELECT FROM_VECTOR(TO_VECTOR('[1.1, 2.2, 3.3]', 3, FLOAT32) );

VECTOR_SERIALIZE(VECTOR('[1.1,2.2,3.3]',3,FLOAT32))
---------------------------------------------------------------
[1.10000002E+000,2.20000005E+000,3.29999995E+000]

1 row selected.

SELECT FROM_VECTOR( TO_VECTOR('[1.1, 2.2, 3.3]', 3, FLOAT32) RETURNING
VARCHAR2(1000));

VECTOR_SERIALIZE(VECTOR('[...]',3,FLOAT32)RETURNINGVARCHAR2(1000))
------------------------------------------------------------------
[1.10000002E+000,2.20000005E+000,3.29999995E+000]

1 row selected.
```

```
SELECT FROM_VECTOR(TO_VECTOR('[1.1, 2.2, 3.3]', 3, FLOAT32) RETURNING CLOB );

VECTOR_SERIALIZE(VECTOR('[...]',3,FLOAT32)RETURNINGCLOB)
--------------------------------------------------------
[1.10000002E+000,2.20000005E+000,3.29999995E+000]

1 row selected.
```

Note:

Applications using Oracle Client 23ai libraries or Thin mode drivers can fetch vector data directly, as shown in the following example:

```
SELECT dataVec FROM vecTab;
```

For applications using pre-Oracle Client 23ai libraries connected to Oracle Database 23ai, use the `FROM_VECTOR()` SQL function to fetch vector data, as shown by the following example:

```
SELECT FROM_VECTOR(dataVec) FROM vecTab;
```

VECTOR_NORM

The `VECTOR_NORM()` function returns the Euclidean norm of a vector `(SQRT(SUM((xi-yi)2)))` in the format of `BINARY_DOUBLE`.

The `VECTOR_NORM()` function returns the Euclidean norm of a vector `(SQRT(SUM((xi-yi)2)))` in the format of `BINARY_DOUBLE`.

For detailed information, see VECTOR_NORM of *Oracle SQL Language Reference*.

VECTOR_DIMENSION_COUNT

The `VECTOR_DIMENSION_COUNT()` function returns the number of dimensions of a vector in the format of an Oracle number.

The `VECTOR_DIMENSION_COUNT()` function returns the number of dimensions of a vector in the format of an Oracle number.

For detailed information, see VECTOR_DIMENSION_COUNT and VECTOR_DIMS of *Oracle SQL Language Reference*.

VECTOR_DIMENSION_FORMAT

The `VECTOR_DIMENSION_FORMAT()` returns the storage format of the vector. It returns a `VARCHAR2`, which can be one of the following values: `'INT8'`, `'FLOAT32'`, or `'FLOAT64'`.

The `VECTOR_DIMENSION_FORMAT()` returns the storage format of the vector. It returns a `VARCHAR2`, which can be one of the following values: `'INT8'`, `'FLOAT32'`, or `'FLOAT64'`.

For detailed information, see VECTOR_DIMENSION_FORMAT of *Oracle SQL Language Reference*.

Oracle AI Vector Search SQL Functions

Oracle AI Vector utilities provide the `VECTOR_CHUNKS` and `VECTOR_EMBEDDING` SQL functions for chunking and embedding data, respectively.

For detailed information, see the following sections in *Oracle Database SQL Language Reference*:

- VECTOR_CHUNKS

  The `VECTOR_CHUNKS` function enables you to split plain text into chunks (pieces of words, sentences, or paragraphs) in preparation for the generation of embeddings, to be used with a vector index.
- VECTOR_EMBEDDING

  The `VECTOR_EMBEDDING` function enables you to generate embedding for different data types according to an embedding ONNX model.

7
Query Data with Similarity Searches

Use Oracle AI Vector Search native SQL operations from your development environment to combine similarity with relational searches.

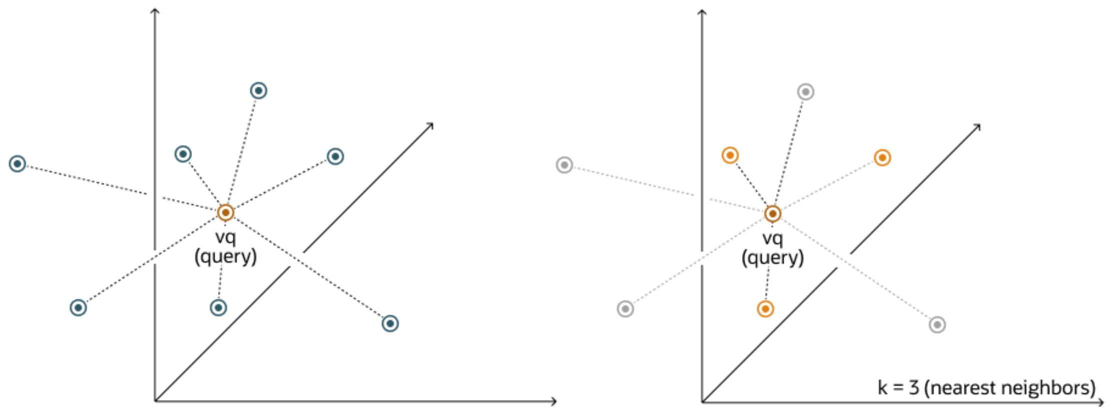
- Perform Exact Similarity Search
  A similarity search looks for the relative order of vectors compared to a query vector. Naturally, the comparison is done using a particular distance metric but what is important is the result set of your top closest vectors, not the distance between them.
- Perform Approximate Similarity Search Using Vector Indexes
  For a vector search to be useful, it needs to be fast and accurate. Approximate similarity searches seek a balance between these goals.
- Perform Multi-Vector Similarity Search
  Another major use-case of vector search is multi-vector search. Multi-vector search is typically associated with a multi-document search, where documents are split into chunks that are individually embedded into vectors.

Perform Exact Similarity Search

A similarity search looks for the relative order of vectors compared to a query vector. Naturally, the comparison is done using a particular distance metric but what is important is the result set of your top closest vectors, not the distance between them.

As an example, and given a certain query vector, you can calculate its distance to all other vectors in your data set. This type of search, also called flat search, or exact search, produces the most accurate results with perfect search quality. However, this comes at the cost of significant search times. This is illustrated by the following diagrams:

Figure 7-1 Exact Search



With an exact search, you compare the query vector `vq` against every other vector in your space by calculating its distance to each vector. After calculating all of these distances, the search returns the nearest k of those as the nearest matches. This is called a k-nearest neighbors (kNN) search.

For example, the Euclidean similarity search involves retrieving the top-k nearest vectors in your space relative to the Euclidean distance metric and a query vector. Here's an example that retrieves the top 10 vectors from the vector_tab table that are the nearest to query_vector using the following exact similarity search query:

```
SELECT docID
FROM vector_tab
ORDER BY VECTOR_DISTANCE( embedding, :query_vector, EUCLIDEAN )
FETCH EXACT FIRST 10 ROWS ONLY;
```

In this example, docID and embedding are columns defined in the vector_tab table and embedding has the VECTOR data type.

In the case of Euclidean distances, comparing squared distances is equivalent to comparing distances. So, when ordering is more important than the distance values themselves, the Euclidean Squared distance is very useful as it is faster to calculate than the Euclidean distance (avoiding the square-root calculation). Consequently, it is simpler and faster to rewrite the query like this:

```
SELECT docID
FROM vector_tab
ORDER BY VECTOR_DISTANCE( embedding, :query_vector, EUCLIDEAN_SQUARED)
FETCH FIRST 10 ROWS ONLY;
```

Note that EXACT is optional.

Note:

Ensure that you use the distance function that was used to train your embedding model.

See Also:

Oracle Database SQL Language Reference for the full syntax of the ROW_LIMITING_CLAUSE

Perform Approximate Similarity Search Using Vector Indexes

For a vector search to be useful, it needs to be fast and accurate. Approximate similarity searches seek a balance between these goals.

- Understand Approximate Similarity Search Using Vector Indexes
  For faster search speeds with large vector spaces, you can use approximate similarity search using vector indexes.
- Optimizer Plans for Vector Indexes
  Optimizer plans for HNSW and IVF indexes are described in the following sections.
- Approximate Similarity Search Examples
  Review these examples to see how you can perform an approximate similarity search using vector indexes.

Understand Approximate Similarity Search Using Vector Indexes

For faster search speeds with large vector spaces, you can use approximate similarity search using vector indexes.

Using vector indexes for a similarity search is called an **approximate search**. Approximate searches use **vector indexes**, which trade off accuracy for performance.

Approximate search for large vector spaces

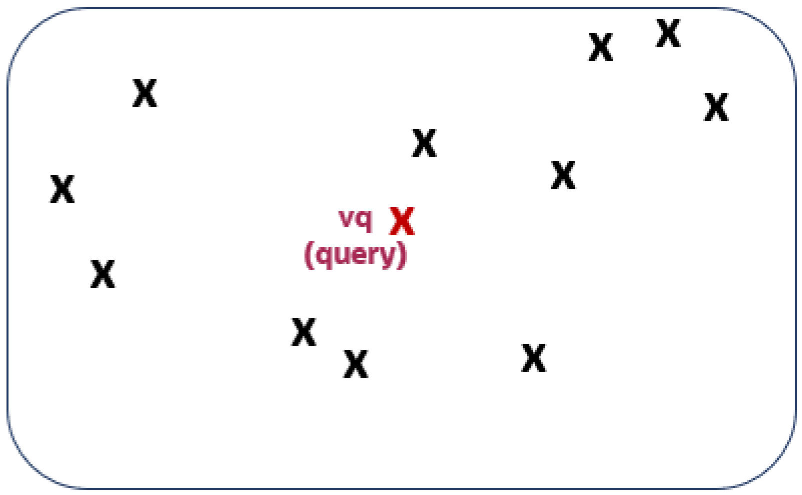
When search quality is your high priority and search speed is less important, Exact Similarity search is a good option. Search speed can be irrelevant for smaller vector spaces, or when you perform searches with high performance servers. However, ML algorithms often perform similarity searches on vector spaces with billions of embeddings. For example, the Deep1B data-set contains 1B images generated by a Convolutional Neural Network (CNN). Computing vector distances with every vector in the corpus to find Top-K matches at 100 percent accuracy is very slow.

Fortunately, there are many types of approximate searches that you can perform using vector indexes. Vector indexes can be less accurate, but they can consume less resources, and can be more efficient. Unlike traditional database indexes, vector indexes are constructed and perform searches using heuristic-based algorithms.

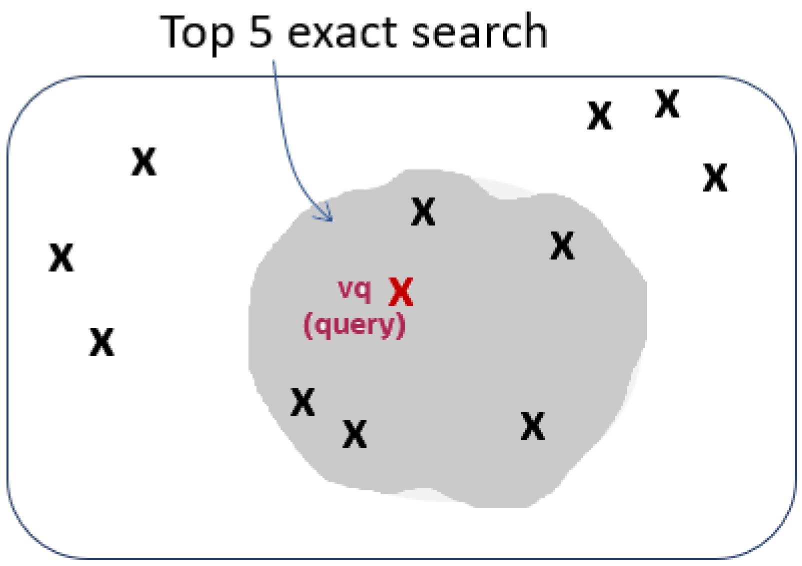
Because 100 percent accuracy cannot be guaranteed by heuristics, vector index searches use **target accuracy**. Internally, the algorithms used for both index creation and index search are doing their best to be as accurate as possible. However, you have the possibility to influence those algorithms by specifying a target accuracy. When creating the index or searching it, you can specify non-default target accuracy values either by specifying a percentage value, or by specifying internal parameters values, depending on the index type you are using.

Target accuracy example

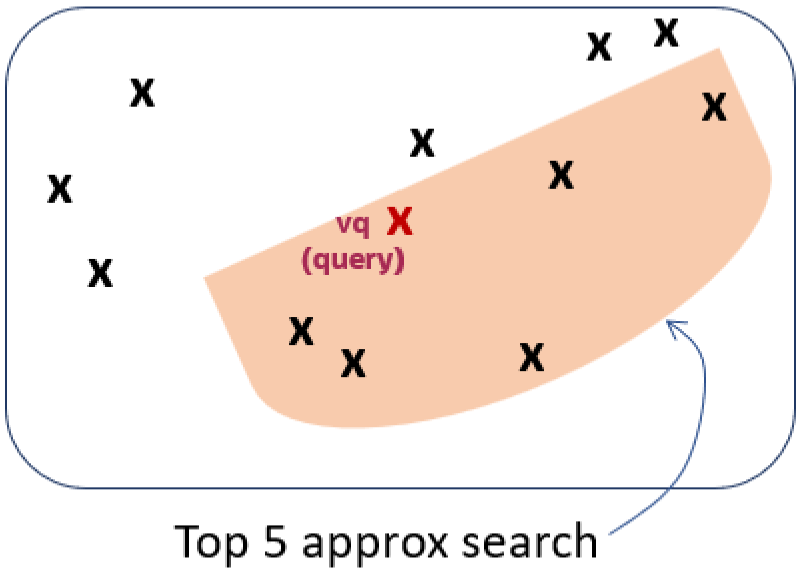
To better understand what is meant by target accuracy look at the following diagrams. The first diagram illustrate a vector space where each vector is represented by a small cross. The one in red represents your query vector.



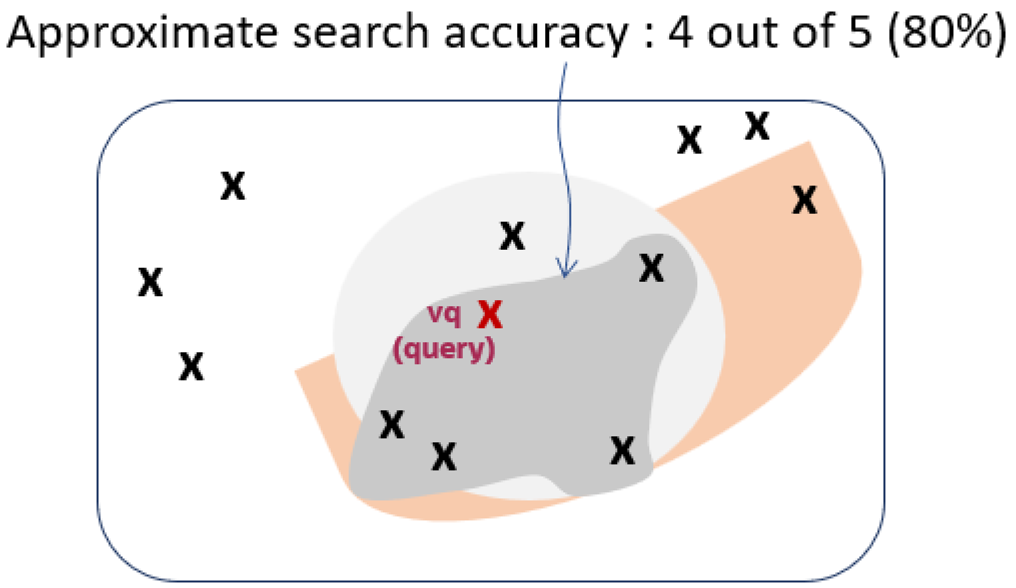
Running a top-5 exact similarity search in that context would return the five vectors shown on the second diagram:



Depending on how your vector index was constructed, running a top-5 approximate similarity search in that context could return the five vectors shown on the third diagram. This is because the index creation process is using heuristics. So searching through the vector index may lead to different results compared to an exact search:



As you can see, the retrieved vectors are different and, in this case, they differ by one vector. This means that, compared to the exact search, the similarity search retrieved 4 out of 5 vectors correctly. The similarity search has 80% accuracy compared to the exact similarity search. This is illustrated on the fourth diagram:



Due to the nature of vector indexes being approximate search structures, it's possible that fewer than K rows are returned in a top-K similarity search.

For information on how to set up your vector indexes, see Create Vector Indexes.

Optimizer Plans for Vector Indexes

Optimizer plans for HNSW and IVF indexes are described in the following sections.

- Optimizer Plans for HNSW Vector Indexes
  A Hierarchical Navigable Small World Graph (HNSW) is a form of In-Memory Neighbor Graph vector index. It is a very efficient index for vector approximate similarity search.
- Optimizer Plans for IVF Vector Indexes
  Inverted File Flat (IVF) is a form of Neighbor Partition Vector index. It is a partition-based index that achieves search efficiency by narrowing the search area through the use of neighbor partitions or clusters.

Optimizer Plans for HNSW Vector Indexes

A Hierarchical Navigable Small World Graph (HNSW) is a form of In-Memory Neighbor Graph vector index. It is a very efficient index for vector approximate similarity search.

In the simplest case, a query has a single table and it does not contain any relational filter predicates or subqueries. The following query example illustrates this situation:

```
SELECT chunk_id, chunk_data
FROM doc_chunks
ORDER BY VECTOR_DISTANCE( chunk_embedding, :query_vector, COSINE )
FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;
```

The corresponding execution plan should look like the following, if the optimizer decides to use the index (start from operation id 5):

Top-K similar vectors are first identified using the HNSW vector index. For each of them, corresponding rows are identified in the base table and required selected columns are extracted.

```
---------------------------------------------------------
| Id  | Operation                         | Name          |
---------------------------------------------------------
|   0 | SELECT STATEMENT                  |               |
|*  1 |  COUNT STOPKEY                    |               |
|   2 |   VIEW                            |               |
|*  3 |    SORT ORDER BY STOPKEY          |               |
|   4 |     TABLE ACCESS BY INDEX ROWID| DOC_CHUNKS    |
|   5 |      VECTOR INDEX HNSW SCAN       | DOCS_HNSW_IDX5 |
---------------------------------------------------------
```

Note:

The Hierarchical Navigable Small World (HNSW) vector index structure contains `rowids` of corresponding base table rows for each vector in the index.

However, your query may contain traditional relational data filters, as illustrated in the following example:

```
SELECT chunk_id, chunk_data
FROM doc_chunks
```

```
WHERE doc_id=1
ORDER BY VECTOR_DISTANCE( chunk_embedding, :query_vector, COSINE )
FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;
```

In that case, there are essentially two main alternatives for the optimizer to generate an execution plan using an HNSW vector index. These two alternatives are called **pre-filtering** and **in-filtering**.

The main difference between pre-filtering and in-filtering are:

- *Pre-filtering* runs the filtering evaluation on the base table first and only traverses the HNSW vector index for corresponding vectors. This can be very fast if the filter predicates are selective (that is, most rows filtered out).
- *In-filtering*, on the other hand, starts by traversing the HNSW vector index and invokes the filtering only for each vector matching candidate. This can be better than pre-filtering when more rows pass the filter predicates. In this case, the number of vector candidates to consider, while traversing the HNSW vector index, might be much less than the number of rows that pass the filters.

For both in-filtering and pre-filtering, the optimizer may choose to process projected columns from your select list before or after the similarity search operation. If it does so after, this is called a join-back operation. If it does so before, it is called a no-join-back operation. The tradeoff between the two depends on the number of rows returned by the similarity search.

The following plan shows one of the four possibilities just described. Specifically, it shows the execution plan when in-filtering is chosen with join back.

In-filter With Join-back (Start from Operation id 5)

HNSW vector index is traversed first, and for each identified vector, filters on the base table for the corresponding `rowid` are applied. Once the top-K `rowids` passing the filters are identified, base table columns are extracted.

```
----------------------------------------------------------------
| Id  | Operation                          | Name             |
----------------------------------------------------------------
|   0 | SELECT STATEMENT                   |                  |
|*  1 |  COUNT STOPKEY                     |                  |
|   2 |   VIEW                             |                  |
|*  3 |    SORT ORDER BY STOPKEY           |                  |
|*  4 |     TABLE ACCESS BY INDEX ROWID    | DOC_CHUNKS       |
|   5 |      VECTOR INDEX HNSW SCAN IN-FILTER| DOCS_HNSW_IDX3   |
|   6 |       VIEW                         | VW_HIJ_B919B0A0  |
|*  7 |        TABLE ACCESS BY USER ROWID  | DOC_CHUNKS       |
----------------------------------------------------------------
```

HNSW Indexes in the Optimizer Plan

HNSW indexes plans may use an internal table and associated index to store index information like mapping between vector `ids` and `rowids`. Mainly `VECTOR$<`*`index name`*`>$HNSW_ROWID_VID_MAP`.

Table 7-1 HNSW Options

Operation	Options	Object_name
TABLE ACCESS	FULL	`VECTOR$<`*`index-name`*`>$HNSW_ROW_VID_MAP`
TABLE ACCESS	STORAGE FULL	`VECTOR$<`*`index-name`*`>$HNSW_ROW_VID_MAP`

For the HNSW index itself, which is an In-Memory object, the plan uses a `VECTOR INDEX` operation. The object name `GALAXIES_HSNW_INX` is provided as an example of the user-specified HNSW index name:

Operation	Options	Object_name
VECTOR INDEX	HNSW SCAN	`GALAXIES_HSNW_INX`
VECTOR INDEX	HNSW SCAN PRE-FILTER	`GALAXIES_HSNW_INX`
VECTOR INDEX	HNSW SCAN IN-FILTER	`GALAXIES_HSNW_INX`

Optimizer Plans for IVF Vector Indexes

Inverted File Flat (IVF) is a form of Neighbor Partition Vector index. It is a partition-based index that achieves search efficiency by narrowing the search area through the use of neighbor partitions or clusters.

Consider the following query:

```
SELECT chunk_id, chunk_data,
FROM doc_chunks
WHERE doc_id=1
ORDER BY VECTOR_DISTANCE( chunk_embedding, :query_vector, COSINE )
FETCH APPROX FIRST 4 ROWS ONLY WITH TARGET ACCURACY 80;
```

The preceding query can lead to the following execution plan:

- Plan line ids 5 to 9: This part happens first. The optimizer chooses the centroid `ids` that are closest to the query vector.
- Plan line ids 10 to 13: With these lines, the base table is joined to the identified centroid partitions. The base table is scanned to look for all the rows that pass the `WHERE` clause filter.
- Plan line id 4: Once both sets are identified, the rows are joined to extract only the relevant ones.
- Plan line id 3: This step extracts the top-K rows.

```
-----------------------------------------------------------------------
--------------------------------------------
| Id  | Operation                               |
Name                                                                |
-----------------------------------------------------------------------
--------------------------------------------
|   0 | SELECT STATEMENT
|                                                                  |
|*  1 |  COUNT STOPKEY
|                                                                  |
|   2 |   VIEW
|                                                                  |
|*  3 |    SORT ORDER BY STOPKEY
|                                                                  |
|*  4 |     HASH JOIN
|                                                                  |
|   5 |      VIEW                            |
VW_IVCR_2D77159E                                                 |
|*  6 |       COUNT STOPKEY
|                                                                  |
|   7 |        VIEW                          |
VW_IVCN_9A1D2119                                                 |
|*  8 |         SORT ORDER BY STOPKEY
|                                                                  |
|   9 |          TABLE ACCESS FULL           |
VECTOR$DOCS_IVF_IDX2$81357_82648_0$IVF_FLAT_CENTROIDS            |
|  10 |      NESTED LOOPS
|                                                                  |
|* 11 |       TABLE ACCESS FULL              |
DOC_CHUNKS                                                       |
|  12 |       TABLE ACCESS BY GLOBAL INDEX ROWID|
VECTOR$DOCS_IVF_IDX2$81357_82648_0$IVF_FLAT_CENTROID_PARTITIONS |
|* 13 |        INDEX UNIQUE SCAN             |
SYS_C008661                                                      |
-----------------------------------------------------------------------------
--------------------------------------
```

IVF Indexes in the Optimizer Plan

If the IVF index is used by the optimizer, the plan contains the names of the centroids and centroid partitions tables accessed as well as corresponding indexes.

The value displayed in the `Options` column for tables accessed via IVF indexes depends upon whether the table scan is for a regular table or Exadata table.

Table 7-2 Centroids and Centroid Partition Table Options

Operation	Options	Object_name

TABLE ACCESS	FULL	`VECTOR$`*`<vector-index-name>`*`$<id>$IVF_FLAT_CENTROIDS`
		`VECTOR$DOCS_IVF_IDX2$<id>$IVF_FLAT_CENTROID_PARTITIONS`

TABLE ACCESS	STORAGE FULL	`VECTOR$<vector-index-name>$<id>$IVF_FLAT_CENTROIDS`
		`VECTOR$DOCS_IVF_IDX2$<id>$IVF_FLAT_CENTROID_PARTITIONS`

Approximate Similarity Search Examples

Review these examples to see how you can perform an approximate similarity search using vector indexes.

- Approximate Search Using HNSW
  This example shows how you can create the Hierarchical Navigable Small World (HNSW) index and run an approximate search using that index.
- Approximate Search Using IVF
  This example shows how you can create the Inverted File Flat (IVF) index and run an approximate search using that index.

Approximate Search Using HNSW

This example shows how you can create the Hierarchical Navigable Small World (HNSW) index and run an approximate search using that index.

```
create table galaxies (id number, name varchar2(50), doc
varchar2(500), embedding vector(5,INT8));

insert into galaxies values (1, 'M31', 'Messier 31 is a barred spiral
galaxy in the Andromeda constellation which has a lot of barred spiral
galaxies.', '[0,2,2,0,0]');
insert into galaxies values (2, 'M33', 'Messier 33 is a spiral galaxy
in the Triangulum constellation.', '[0,0,1,0,0]');
insert into galaxies values (3, 'M58', 'Messier 58 is an intermediate
barred spiral galaxy in the Virgo constellation.', '[1,1,1,0,0]');
insert into galaxies values (4, 'M63', 'Messier 63 is a spiral galaxy
in the Canes Venatici constellation.', '[0,0,1,0,0]');
insert into galaxies values (5, 'M77', 'Messier 77 is a barred spiral
galaxy in the Cetus constellation.', '[0,1,1,0,0]');
insert into galaxies values (6, 'M91', 'Messier 91 is a barred spiral
galaxy in the Coma Berenices constellation.', '[0,1,1,0,0]');
insert into galaxies values (7, 'M49', 'Messier 49 is a giant
elliptical galaxy in the Virgo constellation.', '[0,0,0,1,1]');
insert into galaxies values (8, 'M60', 'Messier 60 is an elliptical
galaxy in the Virgo constellation.', '[0,0,0,0,1]');
insert into galaxies values (9, 'NGC1073', 'NGC 1073 is a barred
spiral galaxy in Cetus constellation.', '[0,1,1,0,0]');

...

commit;
```

In the galaxies example, this is how you can create the HNSW index and how you would run an approximate search using that index:

```
CREATE VECTOR INDEX galaxies_hnsw_idx ON galaxies (embedding)
ORGANIZATION INMEMORY NEIGHBOR GRAPH
DISTANCE COSINE
WITH TARGET ACCURACY 95;
```

```
SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]'), COSINE )
FETCH APPROXIMATE FIRST 3 ROWS ONLY;
```

This approximate search example inherits a target accuracy of 95 as it is set when the index is defined. You could override the `TARGET ACCURACY` of your search by running the following query examples:

```
SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]'), COSINE  )
FETCH APPROXIMATE FIRST 3 ROWS ONLY WITH TARGET ACCURACY 90;


SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]'), COSINE  )
FETCH APPROXIMATE FIRST 3 ROWS ONLY WITH TARGET ACCURACY PARAMETERS
(efsearch 500);
```

You can also create the index using the following syntax:

```
CREATE VECTOR INDEX galaxies_hnsw_idx ON galaxies (embedding) ORGANIZATION
INMEMORY NEIGHBOR GRAPH
DISTANCE COSINE
WITH TARGET ACCURACY 90 PARAMETERS (type HNSW, neighbors 40, efconstruction
500);
```

See Also:

Oracle Database SQL Language Reference for the full syntax of the `ROW_LIMITING_CLAUSE`

Approximate Search Using IVF

This example shows how you can create the Inverted File Flat (IVF) index and run an approximate search using that index.

```
create table galaxies (id number, name varchar2(50), doc varchar2(500),
embedding vector(5,INT8));

insert into galaxies values (1, 'M31', 'Messier 31 is a barred spiral galaxy
in the Andromeda constellation which has a lot of barred spiral galaxies.',
'[0,2,2,0,0]');
insert into galaxies values (2, 'M33', 'Messier 33 is a spiral galaxy in the
Triangulum constellation.', '[0,0,1,0,0]');
insert into galaxies values (3, 'M58', 'Messier 58 is an intermediate
barred spiral galaxy in the Virgo constellation.', '[1,1,1,0,0]');
insert into galaxies values (4, 'M63', 'Messier 63 is a spiral galaxy
in the Canes Venatici constellation.', '[0,0,1,0,0]');
insert into galaxies values (5, 'M77', 'Messier 77 is a barred spiral
galaxy in the Cetus constellation.', '[0,1,1,0,0]');
insert into galaxies values (6, 'M91', 'Messier 91 is a barred spiral
galaxy in the Coma Berenices constellation.', '[0,1,1,0,0]');
insert into galaxies values (7, 'M49', 'Messier 49 is a giant
elliptical galaxy in the Virgo constellation.', '[0,0,0,1,1]');
insert into galaxies values (8, 'M60', 'Messier 60 is an elliptical
galaxy in the Virgo constellation.', '[0,0,0,0,1]');
insert into galaxies values (9, 'NGC1073', 'NGC 1073 is a barred
spiral galaxy in Cetus constellation.', '[0,1,1,0,0]');

...

commit;
```

In the galaxies example, this is how you can create the IVF index and how you can run an approximate search using that index:

```
CREATE VECTOR INDEX galaxies_ivf_idx ON galaxies (embedding)
ORGANIZATION NEIGHBOR PARTITIONS
DISTANCE COSINE
WITH TARGET ACCURACY 95;

SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]'), COSINE )
FETCH APPROXIMATE FIRST 3 ROWS ONLY;
```

If the index is used by the optimizer, then this approximate search example inherits a target accuracy of `95` as it is set when the index is defined. You can override the `TARGET ACCURACY` of your search by running the following query examples:

```
SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]'), COSINE )
FETCH APPROXIMATE FIRST 3 ROWS ONLY WITH TARGET ACCURACY 90;


SELECT name
FROM galaxies
WHERE name <> 'NGC1073'
ORDER BY VECTOR_DISTANCE( embedding, to_vector('[0,1,1,0,0]') )
FETCH APPROXIMATE FIRST 3 ROWS ONLY WITH TARGET ACCURACY PARAMETERS
( NEIGHBOR PARTITION PROBES 10 );
```

You can also create the index using the following syntax:

```
CREATE VECTOR INDEX galaxies_ivf_idx ON galaxies (embedding) ORGANIZATION
NEIGHBOR PARTITIONS
DISTANCE COSINE
WITH TARGET ACCURACY 90 PARAMETERS (type IVF, neighbor partitions 100);
```

See Also:

Oracle Database SQL Language Reference for the full syntax of the `ROW_LIMITING_CLAUSE`

Perform Multi-Vector Similarity Search

Another major use-case of vector search is multi-vector search. Multi-vector search is typically associated with a multi-document search, where documents are split into chunks that are individually embedded into vectors.

A multi-vector search consists of retrieving top-K vector matches using grouping criteria known as partitions based on the documents' characteristics. This ability to score documents based on the similarity of their chunks to a query vector being searched is facilitated in SQL using the partitioned row limiting clause.

With multi-vector search, it is easier to write SQL statements to answer the following type of question:

- If they exist, what are the four best matching sentences found in the three best matching paragraphs of the two best matching books?

For example, imagine if each book in your database is organized into paragraphs containing sentences which have vector embedding representations, then you can answer the previous question using a single SQL statement such as:

```
SELECT bookId, paragraphId, sentence
FROM books
ORDER BY vector_distance(sentence_embedding, :sentence_query_vector)
FETCH FIRST 2 PARTITIONS BY bookId, 3 PARTITIONS BY paragraphId, 4 ROWS ONLY;
```

You can also use an approximate similarity search instead of an exact similarity search as shown in the following example:

```
SELECT bookId, paragraphId, sentence
FROM books
ORDER BY vector_distance(sentence_embedding, :sentence_query_vector)
FETCH APPROXIMATE FIRST 2 PARTITIONS BY bookId, 3 PARTITIONS BY paragraphId,
4 ROWS ONLY
WITH TARGET ACCURACY 90;
```

Note:

All the rows returned are ordered by `VECTOR_DISTANCE()` and not grouped by the partition clause.

Semantically, the previous SQL statement is interpreted as:

- Sort all records in the books table in descending order of the vector distance between the sentences and the query vector.
- For each record in this order, check its `bookId` and `paragraphId`. This record is produced if the following three conditions are met:
  1. Its `bookId` is one of the first two distinct `bookId` in the sorted order.
  2. Its `paragraphId` is one of the first three distinct `paragraphId` in the sorted order within the same `bookId`.
  3. Its record is one of the first four records within the same `bookId` and `paragraphId` combination.
- Otherwise, this record is filtered out.

Multi-vector similarity search is not just for documents and can be used to answer the following questions too:

- Return the top K closest matching photos but ensure that they are photos of different people.
- Find the top K songs with two or more audio segments that best match this sound snippet.

Note:

- This partition row-limiting clause extension is a generic extension of the SQL language. It does not have to apply just to vector searches.
- Multi-vector search with the partitioning row-limit clause does not use vector indexes.

See Also:

Oracle Database SQL Language Reference for the full syntax of the `ROW_LIMITING_CLAUSE`

8

Work with Retrieval Augmented Generation

Oracle AI Vector Search supports Enterprise Retrieval Augmented Generation (RAG) to enable sophisticated queries that can combine vectors with relational data, graph data, spatial data, and JSON collections. By communicating with LLMs through the implementation of RAG, the knowledge of LLMs is increased with business data found through AI Vector Search.

- Compliment LLMs with Oracle AI Vector Search
  Using Retrieval Augmented Generation (RAG) can mitigate the inaccuracies and hallucinations faced when using Large Language Models (LLMs). Oracle AI Vector Search enables RAG through the use of popular frameworks and PL/SQL APIs.
- SQL RAG Example
  This scenario allows you to run a similarity search for specific documentation content based on a user query. Once documentation chunks are retrieved, they are concatenated and a prompt is generated to ask an LLM to answer the user question using retrieved chunks.

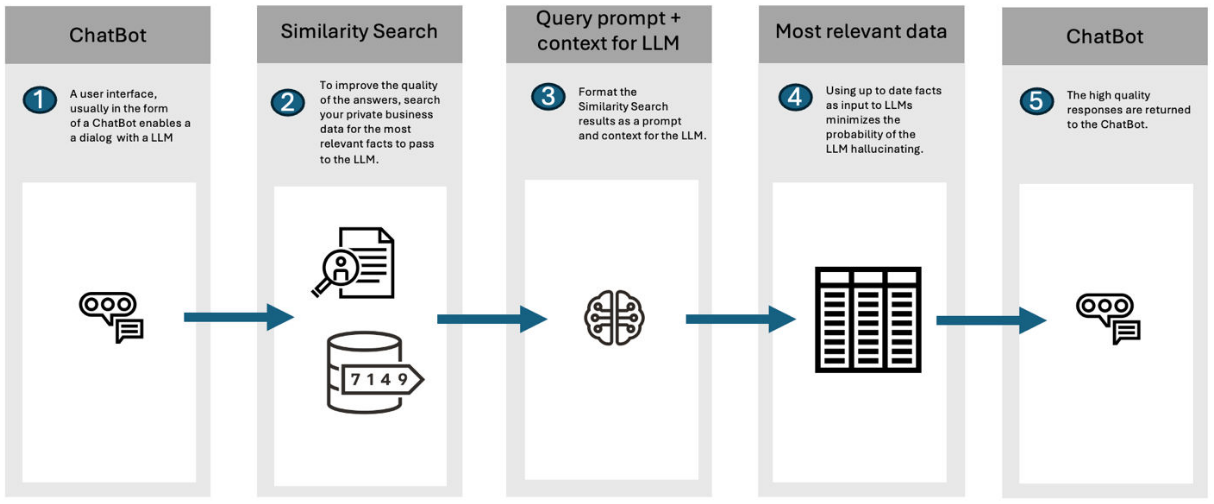
Compliment LLMs with Oracle AI Vector Search

Using Retrieval Augmented Generation (RAG) can mitigate the inaccuracies and hallucinations faced when using Large Language Models (LLMs). Oracle AI Vector Search enables RAG through the use of popular frameworks and PL/SQL APIs.

The primary problem with Large Language Models (LLMs) like GPT (Generative Pretrained Transformer) is that they generate responses based solely on the patterns and data they were trained on up to the point of their last update. This means that they inherently lack the ability to access or incorporate new, real-time information after their training is cut off, potentially limiting their responses to outdated or incomplete information. LLMs do not know about your private company data. Consequently, LLMs can make up answers (hallucinate) when they do not have enough relevant and up-to-date facts.

By providing your LLM with up-to-date facts from your company, you can minimize the probability that an LLM will make up answers (hallucinate).

Figure 8-1 Example RAG Workflow


ChatBot
1
A user interface, usually in the form of a ChatBot enables a a dialog with a LLM
Similarity Search
2
To improve the quality of the answers, search your private business data for the most relevant facts to pass to the LLM.
7149
Query prompt + context for LLM
3
Format the Similarity Search results as a prompt and context for the LLM.
Most relevant data
4
Using up to date facts as input to LLMs minimizes the probability of the LLM hallucinating.
ChatBot
5
The high quality responses are returned to the ChatBot.

Retrieval Augmented Generation (RAG) is an approach developed to address the limitations of LLMs. RAG combines the strengths of pretrained language models with the ability to retrieve recent and accurate information from a dataset or database in real-time during the generation of responses. Here is how RAG improves upon the issues with traditional LLMs:

- **Access to External and Private Information:** RAG can pull in data from external and private sources during its response generation process. This allows it to provide answers that are up-to-date and grounded in the latest available information, which is crucial for queries requiring current knowledge or specific details not included in its original training data.
- **Factually More Accurate and Detailed Responses:** While traditional LLMs are trained on older data, RAG incorporates real-time retrieved information, meaning that generated responses are not only contextually rich but also factually more up-to-date and accurate as time goes on. This is particularly beneficial for queries that require precision and detail, such as scientific facts, historical data, or specific statistics.
- **Reduced Hallucination:** LLMs can sometimes "hallucinate" information, as in generate plausible but false or unverified content. RAG mitigates this by grounding responses in retrieved documents, thereby enhancing the reliability of the information provided.

Oracle AI Vector Search enables RAG within Oracle Database using the `DBMS_VECTOR_CHAIN` PL/SQL package. Alternatively, you can implement RAG externally by using popular frameworks such as LangChain.

LangChain is a popular open source framework that encapsulates popular LLMs, vector databases, document stores, and embedding models. `DBMS_VECTOR_CHAIN` is a PL/SQL package that provides the ability to create RAG solutions, all within the database. With `DBMS_VECTOR_CHAIN`, your data never needs to leave the security of Oracle Database.

See Also:

- *Oracle Database PL/SQL Packages and Types Reference* for details about the `DBMS_VECTOR_CHAIN` package

SQL RAG Example

This scenario allows you to run a similarity search for specific documentation content based on a user query. Once documentation chunks are retrieved, they are concatenated and a prompt is generated to ask an LLM to answer the user question using retrieved chunks.

1. Start SQL*Plus and connect to Oracle Database as a local test user.
   a. Log in to SQL*Plus as the `sys` user, connecting as `sysdba`:

      ```
      conn sys/password AS sysdba


      SET SERVEROUTPUT ON;
      SET ECHO ON;
      SET LONG 100000;
      ```

   b. Create a local test user (`vector`) and grant necessary privileges:

      ```
      DROP USER vector cascade;


      CREATE USER vector identified by <my vector password>


      GRANT DB_DEVELOPER_ROLE, CREATE CREDENTIAL TO vector;
      ```

   c. Set the proxy if one exists:

      ```
      EXEC UTL_HTTP.SET_PROXY('<my proxy full name>:<my proxy port>');
      ```

   d. Grant connect privilege for a host using the `DBMS_NETWORK_ACL_ADMIN` procedure. This example uses `*` to allow any host. However, you can explicitly specify each host that you want to connect to.

      ```
      BEGIN
        DBMS_NETWORK_ACL_ADMIN.APPEND_HOST_ACE(
          host => '*',
          ace => xs$ace_type(privilege_list => xs$name_list('connect'),
                             principal_name => 'VECTOR',
                             principal_type => xs_acl.ptype_db));
      END;
      /
      ```

e. Connect to Oracle Database as the test user.

```
conn docuser/password;
```

2. Create a credential for Oracle Cloud Infrastructure Generative AI:

   a. Run `DBMS_VECTOR_CHAIN.CREATE_CREDENTIAL` to create and store an OCI credential (`OCI_CRED`).

   OCIGenAI requires the following parameters:

```
{
"user_ocid": "<user ocid>",
"tenancy_ocid": "<tenancy ocid>",
"compartment_ocid": "<compartment ocid>",
"private_key": "<private key>",
"fingerprint": "<fingerprint>"
}
```

> **Note:**
>
> The generated private key may appear as:
>
> ```
> -----BEGIN RSA PRIVATE KEY-----
> <private key string>
> -----END RSA PRIVATE KEY-----
> ```
>
> You pass the `<private key string>` value (excluding the `BEGIN` and `END` lines), either as a single line or as multiple lines.

```
BEGIN
  DBMS_VECTOR_CHAIN.DROP_CREDENTIAL(credential_name =>
'OCI_CRED');
EXCEPTION
  WHEN OTHERS THEN NULL;
END;
/


DECLARE
  jo json_object_t;
BEGIN
  jo := json_object_t();
  jo.put('user_ocid', '<user ocid>');
  jo.put('tenancy_ocid', '<tenancy ocid>');
  jo.put('compartment_ocid', '<compartment ocid>');
  jo.put('private_key', '<private key>');
  jo.put('fingerprint', '<fingerprint>');
  DBMS_OUTPUT.PUT_LINE(jo.to_string);
  DBMS_VECTOR_CHAIN.CREATE_CREDENTIAL(
    credential_name => 'OCID_CRED',
```

```
        params          => json(jo.to_string));
    END;
    /
```

b. Check credential creation:

```
col owner format a15
col credential_name format a20
col username format a20


SELECT owner, credential_name, username
FROM all_credentials
ORDER BY owner, credential_name, username;
```

3. Generate a prompt using similarity search results:

```
SET SERVEROUTPUT ON;

VAR prompt CLOB;
VAR user_question CLOB;
VAR context CLOB;

BEGIN
  -- initialize the concatenated string
  :context := '';

  -- read this question from the user
  :user_question := 'what are vector indexes?';

  -- cursor to fetch chunks relevant to the user's query
  FOR rec IN (SELECT EMBED_DATA
              FROM DOC_ID = 'Vector User Guide'
              ORDER BY vector_distance(embed_vector, vector_embedding(
                  doc_model using :user_question as input), COSINE)
              FETCH EXACT FIRST 10 ROWS ONLY)
  LOOP
    -- concatenate each value to the string
    :context := :context || rec.embed_data;
  END LOOP;

  -- concatenate strings and format it as an enhanced prompt to the LLM
  :prompt := 'Answer the following question using the supplied context
                assuming you are a subject matter expert. Question: '
                || :user_question || ' Context: ' || :context;

  DBMS_OUTPUT.PUT_LINE('Generated prompt: ' || :prompt);
END;
/
```

4. Issue the GenAI call:

```
DECLARE
  input CLOB;
  params CLOB;
  output CLOB;
BEGIN
  input := :prompt;
  params := '{
    "provider" : "ocigenai",
    "credential_name" : "OCI_CRED",
    "url" : https://inference.generativeai.us-chicago-1.oci.
            oraclecloud.com/20231130/actions/generateText,
    "model" : "cohere.command"
  }';

  output := DBMS_VECTOR_CHAIN.UTL_TO_GENERATE_TEXT(input,
json(params));
  DBMS_OUTPUT.PUT_LINE(output);
  IF output IS NOT NULL THEN
    DBMS_LOB.FREETEMPORARY(output);
  END IF;
EXCEPTION
  WHEN OTHERS THEN
    DBMS_OUTPUT.PUT_LINE(SQLERRM);
    DBMS_OUTPUT.PUT_LINE(SQLCODE);
END;
/
```

9 Supported Clients and Languages

For more information about Oracle AI Vector Search support using some of Oracle's available clients and languages, see the included reference material.

Clients and Languages	Reference Material
PL/SQL	*Oracle Database PL/SQL Language Reference*
MLE JavaScript	*Oracle Database JavaScript Developer's Guide*
JDBC	*Oracle Database JDBC Developer's Guide*
Node.js	node-oracledb documentation
Python	python-oracledb documentation
Oracle Call Interface	*Oracle Call Interface Developer's Guide*
ODP.NET	*Oracle Data Provider for .NET Developer's Guide.*
SQL*Plus	*SQL*Plus User's Guide and Reference*

Oracle Database 23ai supports binding with native VECTOR types for all Oracle clients. Applications that use earlier Oracle Client 23ai libraries can connect to Oracle Database 23ai in the following ways:

- Using the `TO_VECTOR()` SQL function to insert vector data, as shown in the following example:

  ```
  INSERT INTO vecTab VALUES(TO_VECTOR('[1.1, 2.9, 3.14]'));
  ```

- Using the `FROM_VECTOR()` SQL function to fetch vector data, as shown in the following example:

  ```
  SELECT FROM_VECTOR(dataVec) FROM vecTab;
  ```

10

Vector Diagnostics

AI Vector Search includes several views, statistics, and parameters that can be used to help understand how vector search is performing for your workload.

- Oracle AI Vector Search Views
  These are a set of data dictionary views related to Oracle AI Vector Search.
- Oracle AI Vector Search Statistics
  These are a set of statistics related to Oracle AI Vector Search.
- Oracle AI Vector Search Parameters
  This is a set of parameters related to Oracle AI Vector Search.

Oracle AI Vector Search Views

These are a set of data dictionary views related to Oracle AI Vector Search.

- Vector Utilities-Related Views
  These views display language-specific data (abbreviation token details) and vocabulary data related to the Oracle AI Vector Search SQL and PL/SQL utilities.
- Vector Memory Pool Views
  Review the various vector memory pool views.
- Vector Index Views
  Review the vector index views.

Vector Utilities-Related Views

These views display language-specific data (abbreviation token details) and vocabulary data related to the Oracle AI Vector Search SQL and PL/SQL utilities.

- ALL_VECTOR_ABBREV_TOKENS
  The `ALL_VECTOR_ABBREV_TOKENS` view displays a list of abbreviation tokens from all supported languages.
- ALL_VECTOR_LANG
  The `ALL_VECTOR_LANG` view displays a list of all supported languages, distributed by default.
- USER_VECTOR_ABBREV_TOKENS
  The `USER_VECTOR_ABBREV_TOKENS` view displays a list of abbreviation tokens from all languages loaded by the current user.
- USER_VECTOR_LANG
  The `USER_VECTOR_LANG` view displays all languages loaded by the current user.
- USER_VECTOR_VOCAB
  The `USER_VECTOR_VOCAB` view displays all custom token vocabularies created by the current user.

- USER_VECTOR_VOCAB_TOKENS
  The `USER_VECTOR_VOCAB_TOKENS` view displays tokens from all custom token vocabularies created by the current user.
- ALL_VECTOR_VOCAB
  The `ALL_VECTOR_VOCAB` view displays all custom token vocabularies.
- ALL_VECTOR_VOCAB_TOKENS
  The `ALL_VECTOR_VOCAB_TOKENS` view displays tokens from all custom token vocabularies.

Related Topics

- *Oracle Database PL/SQL Packages and Types Reference*

ALL_VECTOR_ABBREV_TOKENS

The `ALL_VECTOR_ABBREV_TOKENS` view displays a list of abbreviation tokens from all supported languages.

Column Name	Data Type	Description
`ABBREV_OWNER`	`VARCHAR2(128)`	Owner of the abbreviation token (for example, `PUBLIC`)
`ABBREV_LANGUAGE`	`NUMBER`	Language ID for the language (for example, `1` for American)
`ABBREV_TOKEN`	`NVARCHAR2(255)`	List of all abbreviation tokens corresponding to each language

ALL_VECTOR_LANG

The `ALL_VECTOR_LANG` view displays a list of all supported languages, distributed by default.

Column Name	Data Type	Description
`LANG_OWNER`	`VARCHAR2(128)`	Owner of the language (for example, `PUBLIC`)
`LANG_LANG`	`NUMBER`	Language ID for the language (for example, `1` for American)
`LANG_NAME`	`VARCHAR2(128)`	Name of the language (for example, `AMERICAN`)

USER_VECTOR_ABBREV_TOKENS

The `USER_VECTOR_ABBREV_TOKENS` view displays a list of abbreviation tokens from all languages loaded by the current user.

Column Name	Data Type	Description
`ABBREV_LANGUAGE`	`NUMBER`	Language ID for the language (for example, `1` for American)
`ABBREV_TOKEN`	`NVARCHAR2(255)`	List of all abbreviation tokens corresponding to each language

USER_VECTOR_LANG

The USER_VECTOR_LANG view displays all languages loaded by the current user.

Column Name	Data Type	Description
LANG_LANG	NUMBER	Language ID for the language (for example, 1 for American)
LANG_NAME	VARCHAR2(128)	Name of the language (for example, AMERICAN)

USER_VECTOR_VOCAB

The USER_VECTOR_VOCAB view displays all custom token vocabularies created by the current user.

Column Name	Data Type	Description
VOCAB_NAME	VARCHAR2(128)	User-specified name of the vocabulary (for example, DOC_VOCAB)
FORMAT	VARCHAR2(4)	Format of the vocabulary, such as XLM, BERT, or GPT2
CASED	VARCHAR2(7)	Character-casing of the vocabulary, that is, vocabulary to be treated as cased or uncased

USER_VECTOR_VOCAB_TOKENS

The USER_VECTOR_VOCAB_TOKENS view displays tokens from all custom token vocabularies created by the current user.

Column Name	Data Type	Description
VOCAB_NAME	VARCHAR2(128)	User-specified name of the vocabulary (for example, DOC_VOCAB)
VOCAB_TOKEN	VARCHAR2(255)	Tokens contained in the vocabulary

ALL_VECTOR_VOCAB

The ALL_VECTOR_VOCAB view displays all custom token vocabularies.

Column Name	Data Type	Description
VOCAB_OWNER	VARCHAR2(128)	Owner of the vocabulary (for example, SYS)
VOCAB_NAME	VARCHAR2(128)	User-specified name of the vocabulary (for example, DOC_VOCAB)

Column Name	Data Type	Description
FORMAT	VARCHAR2(4)	Format of the vocabulary, such as XLM, BERT, or GPT2
CASED	VARCHAR2(7)	Character-casing of the vocabulary, that is, vocabulary to be treated as cased or uncased

ALL_VECTOR_VOCAB_TOKENS

The ALL_VECTOR_VOCAB_TOKENS view displays tokens from all custom token vocabularies.

Column Name	Data Type	Description
VOCAB_OWNER	VARCHAR2(128)	Owner of the vocabulary (for example, SYS)
VOCAB_NAME	VARCHAR2(128)	User-specified name of the vocabulary (for example, DOC_VOCAB)
VOCAB_TOKEN	VARCHAR2(255)	Tokens contained in the vocabulary

Vector Memory Pool Views

Review the various vector memory pool views.

- V$VECTOR_MEMORY_POOL
  This view contains information about the space allocation for Vector Memory.

V$VECTOR_MEMORY_POOL

This view contains information about the space allocation for Vector Memory.

The Vector Memory Pool area is used primarily to maintain in-memory vector indexes or metadata useful for vector-related operations. The Vector Memory Pool is subdivided into two pools: a 1MB pool used to store In-Memory Neighbor Graph Index allocations; and a 64K pool used to store metadata. The amount of available memory in each pool is visible in the V$VECTOR_MEMORY_POOL view. The relative size of the two pools is determined by internal heuristics. The size of the Vector Memory Pool is controlled by the vector_memory_size parameter. Area in the Vector Memory Pool is also allocated to accelerate Neighbor Partition Index access by storing centroid vectors.

Column Name	Data Type	Description
POOL	VARCHAR2(26)	Name of the pools in the Vector Memory Pool (64K or 1MB)
ALLOC_BYTES	NUMBER	Total amount of memory allocated to this pool
USED_BYTES	NUMBER	Amount of memory currently used in this pool

Column Name	Data Type	Description
POPULATE_STATUS	VARCHAR2(26)	Status of the vector memory store—whether it is being populated, is done populating etc.
CON_ID	NUMBER	The ID of the container to which the data pertains. Possible values are: • 0: This value is used for rows containing data that pertain to the entire multitenant container database (CDB). This value is also used for rows in non-CDBs. • 1: This value is used for rows containing data that pertain to only the root. • n: Where n is the applicable container ID for the rows containing data.

Example

```
select CON_ID, POOL, ALLOC_BYTES/1024/1024 as ALLOC_BYTES_MB,
USED_BYTES/1024/1024 as USED_BYTES_MB
from V$VECTOR_MEMORY_POOL order by 1,2;


    CON_ID POOL             ALLOC_BYTES_MB USED_BYTES_MB
---------- ---------------- -------------- -------------
         1 1MB POOL                    319             0
         1 64KB POOL                   144             0
         1 IM POOL METADATA             32            32
         2 1MB POOL                    320             0
         2 64KB POOL                   144             0
         2 IM POOL METADATA             16            16
         3 1MB POOL                    320             0
         3 64KB POOL                   144             0
         3 IM POOL METADATA             16            16
         4 1MB POOL                    320             0
         4 64KB POOL                   144             0
         4 IM POOL METADATA             16            16

12 rows selected.

SQL>
```

Vector Index Views

Review the vector index views.

- VECSYS.VECTOR$INDEX
  This dictionary table contains detailed information about vector indexes.

VECSYS.VECTOR$INDEX

This dictionary table contains detailed information about vector indexes.

Column Name	Data Type	Description
`IDX_OBJN`	`NUMBER`	Object number of the vector index
`IDX_OBJD`	`NUMBER`	ID of the vector index object. This ID can be used to rebuild the vector index.
`IDX_OWNER#`	`NUMBER`	Owner ID of the vector index. Refer user$ entry
`IDX_NAME`	`VARCHAR2(128)`	Name of the vector index.
`IDX_BASE_TABLE_OBJN`	`NUMBER`	Base table object number
`IDX_PARAMS`	`JSON`	Vector index creation parameters such as vector column indexed, index distance, vector dimension datatype, number of dimensions, efConstruction, and number of neighbors for in-memory neighbor graph HNSW index or the number of centroids for Inverted Flat Vector Indexes.
`IDX_AUXILIARY_TABLES`	`JSON`	Names and object IDs of auxiliary tables used to support rowid-to-vertexid conversion information or names of a centroid table and its associated partitions table for Inverted Flat File vector indexes.
`IDX_SPARE1`	`NUMBER`	
`IDX_SPARE2`	`JSON`	

Example

```
SQL> SELECT JSON_SERIALIZE(IDX_PARAMS returning varchar2 PRETTY)
  2* FROM VECSYS.VECTOR$INDEX where IDX_NAME = 'DOCS_HNSW_IDX';

JSON_SERIALIZE(IDX_PARAMSRETURNINGVARCHAR2PRETTY)
{
  "type" : "HNSW",
  "num_neighbors" : 32,
  "efConstruction" : 300,
  "upcast_dtype" : 1,
  "distance" : "COSINE",
  "accuracy" : 95,
  "vector_type" : "FLOAT32",
  "vector_dimension" : 384,
  "degree_of_parallelism" : 1,
  "indexed_col" : "EMBED_VECTOR"
}
SQL>
SQL> select * from vecsys.vector$index;

IDX_OBJN IDX_OBJD  IDX_OWNER# IDX_NAME       IDX_BASE_TABLE_OBJN
IDX_PARAMS
IDX_AUXILIARY_TABLES
                           IDX_SPARE1 IDX_SPARE2
-------- --------  ---------- -------------- -------------------
--------------------------
--------------------
                           ----------  ---------
   74051     143                DOCS_HNSW_IDX              73497
{"type":"HNSW",                        {"rowid_vid_map_objn":74052,

"num_neighbors":32,
"shared_journal_transaction_commits_objn":74054,

"efConstruction":300,
"shared_journal_change_log_objn":74057,

"upcast_dtype":1,
"rowid_vid_map_name":"VECTOR$DOCS_HNSW_IDX$HNSW_ROWID_VID_MAP",


"distance":"COSINE",
"shared_journal_transaction_commits_name":"VECTOR$DOCS_HNSW_IDX$HNSW_SHARED_J
OURNAL_TRANSACTION_COMMITS",

"accuracy":95,
"shared_journal_change_log_name":"VECTOR$DOCS_HNSW_IDX$HNSW_SHARED_JOURNAL_CH
ANGE_LOG"}

"vector_type":"FLOAT32",

"vector_dimension":384,

"degree_of_parallelism":1,

"indexed_col":"EMBED_VECTOR"}

   74072      143             GALAXIES_HNSW_IDX           74069
{"type":"HNSW",                         {"rowid_vid_map_objn":74073,

"num_neighbors":32,
"shared_journal_transaction_commits_objn":74075,

"efConstruction":300,
"shared_journal_change_log_objn":74078,

"upcast_dtype":0,
"rowid_vid_map_name":"VECTOR$GALAXIES_HNSW_IDX$HNSW_ROWID_VID_MAP",

"distance":"COSINE",
"shared_journal_transaction_commits_name":"VECTOR$GALAXIES_HNSW_IDX$HNS
W_SHARED_JOURNAL_TRANSACTION_COMMITS",

"accuracy":95,
"shared_journal_change_log_name":"VECTOR$GALAXIES_HNSW_IDX$HNSW_SHARED_
JOURNAL_CHANGE_LOG"}

"vector_type":"INT8",

"vector_dimension":5,

"degree_of_parallelism":1,

"indexed_col":"EMBEDDING"}


SQL>
```

Oracle AI Vector Search Statistics

These are a set of statistics related to Oracle AI Vector Search.

- Oracle AI Vector Search Dictionary Statistics
  A set of dictionary statistics related to Oracle AI Vector Search.
- Oracle Machine Learning Static Dictionary Views
  Lists data dictionary views related to Oracle Machine Learning models.

Oracle AI Vector Search Dictionary Statistics

A set of dictionary statistics related to Oracle AI Vector Search.

- **Vector simd dist single calls**: The number of vector distance function calls invoked by the user, where both the inputs are a single vector.
- **Vector simd dist point calls**: The number of vector distance function calls invoked by the user, where one input is a single vector, and the other input is an array of vectors.
- **Vector simd dist array calls**: The number of vector distance function calls invoked by the user, where both the inputs are an array of vectors.
- **Vector simd dist flex calls**: The number of vector distance function calls invoked by the user, where at least one input is with FLEX vector data type (no dimension or storage data type specified).
- **Vector simd dist total rows:** The number of rows processed by the vector distance function.
- **Vector simd dist flex rows**: The number of rows processed by the vector distance function with FLEX vector data type.
- **Vector simd topK single calls**: The number of `topK` distance function calls invoked by the user, where both the inputs are a single vector.

- **Vector simd topK point calls**: The number of `topK` distance function calls invoked by the user, where one input is a single vector and the other input is an array of vectors.
- **Vector simd topK array calls**: The number of `topK` distance function calls invoked by the user, where both the inputs are an array of vectors.
- **Vector simd topK flex calls**: The number of `topK` distance function calls invoked by the user, where at least one input is with FLEX vector data type (no dimension or storage data type specified).
- **Vector simd topK total rows**: The number of rows processed by the `topK` distance function.
- **Vector simd topK flex rows**: The number of rows processed by the `topK` distance function with FLEX vector data type.
- **Vector simd topK selected total rows**: The number of distance results returned by the `topK` vector distance function.

> **Note:**
>
> This is typically `sum(K)` for all `topK` queries.

- **Vector simd construction num of total calls**: The number of vector construction function calls invoked by the user.
- **Vector simd construction total result rows**: The number of vector rows returned by the vector construction function.
- **Vector simd construction num of ASCII calls**: The number of vector construction function calls invoked by the user, where the input encoding is ASCII.
- **Vector simd construction num of flex calls**: The number of vector construction function calls invoked by the user, where the output vector is of FLEX vector data type.
- **Vector simd construction result rows for flex**: The number of vector rows returned by the vector construction function, where the output vector is of FLEX vector data type.
- **Vector simd vector conversion num of total calls**: The number of vector conversion function calls invoked by the user.
- **VECTOR NEIGHBOR GRAPH HNSW build HT Element Allocated:** The number of hash table elements allocated for vector indexes having organization `Inmemory Neighbor Graph` and type `HNSW` that were created by a user.
- **VECTOR NEIGHBOR GRAPH HNSW build HT Element Freed:** The number of hash table elements freed for vector indexes having organization `Inmemory Neighbor Graph` and type `HNSW` that were created by a user.
- **VECTOR NEIGHBOR GRAPH HNSW reload attempted:** The number of reload operations attempted in the background for vector indexes having organization `Inmemory Neighbor Graph` and type `HNSW`.
- **VECTOR NEIGHBOR GRAPH HNSW reload successful:** The number of reload operations completed in the background for vector indexes having organization `Inmemory Neighbor Graph` and type `HNSW`.
- **VECTOR NEIGHBOR GRAPH HNSW build computed layers:** The total number of layers created in an HNSW index.

- **VECTOR NEIGHBOR GRAPH HNSW build indexed vectors:** The total number of vector indexes in the HNSW index.
- **VECTOR NEIGHBOR GRAPH HNSW build computed distances:** The total number of distance computations executed during the HNSW index build phase.
- **VECTOR NEIGHBOR GRAPH HNSW build sparse layers computed distances:** The total number of distance computations executed during the HNSW index build phase, in all the layers, except the bottom one.
- **VECTOR NEIGHBOR GRAPH HNSW build dense layer computed distances:** The total number of distance computations executed during the HNSW index phase in the bottom layer.
- **VECTOR NEIGHBOR GRAPH HNSW build prune operation computed distances:** The total number of distance computations that were executed during the pruning operations required to find the closest neighbors for a vector in the HNSW index build phase.
- **VECTOR NEIGHBOR GRAPH HNSW build pruned neighbor lists:** The total number of neighbors pruned during the HNSW index build phase.
- **VECTOR NEIGHBOR GRAPH HNSW build pruned neighbors:** The total number of neighbors pruned during the HNSW index build phase.
- **VECTOR NEIGHBOR GRAPH HNSW build created edges:** The total number of edges created in an HNSW index.
- **VECTOR NEIGHBOR GRAPH HNSW search executed approximate:** The total number of query searches executed using approximate search in an HNSW index.
- **VECTOR NEIGHBOR GRAPH HNSW search executed exhaustive:** The total number of query searches executed using exact search in an HNSW index.
- **VECTOR NEIGHBOR GRAPH HNSW search computed distances dense layer:** The total number of distance computations executed in the bottom layer of an HNSW index during query searches.
- **VECTOR NEIGHBOR GRAPH HNSW search computed distances sparse layer:** The total number of distance computations executed in all the layers except the bottom layer of an HNSW index during query searches.
- **VECTOR NEIGHBOR PARTITIONS IVF build HT Element Allocated:** The number of hash table elements allocated for vector indexes having organization `Neighbor Partitions` and type `IVF` that were created by a user.
- **VECTOR NEIGHBOR PARTITIONS IVF build HT Element Freed:** The number of hash table elements freed for vector indexes having organization `Neighbor Partitions` and type `IVF` that were created by a user.
- **VECTOR NEIGHBOR PARTITIONS IVF background Population Started:** The number of in-memory centroids background population operations started for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF background Population Succeeded:** The number of in-memory centroids background population operations completed for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF background Cleanup Started:** The number of in-memory centroids background cleanup operations started for vector indexes having organization `Neighbor Partitions` and type `IVF`.

- **VECTOR NEIGHBOR PARTITIONS IVF XIC Population Started:** The number of in-memory centroids cross-instance population operations started for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF XIC Population Succeeded:** The number of in-memory centroids cross-instance population operations completed for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF XIC Cleanup Started:** The number of in-memory centroids cross-instance cleanup operations started for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF XIC Cleanup Succeeded:** The number of in-memory centroids cross-instance cleanup operations completed for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF im centroids in scan:** The number of times that in-memory centroids are used in scan for vector indexes having organization `Neighbor Partitions` and type `IVF`.
- **VECTOR NEIGHBOR PARTITIONS IVF im centroids in dmls:** The number of times that in-memory centroids are used in the DML that happens on the base table with vector indexes having organization `Neighbor Partitions` and type `IVF`.

Oracle Machine Learning Static Dictionary Views

Lists data dictionary views related to Oracle Machine Learning models.

Query the following views to learn more about the machine learning models:

- ALL_MINING_MODEL_ATTRIBUTES
- ALL_MINING_MODELS

Oracle AI Vector Search Parameters

This is a set of parameters related to Oracle AI Vector Search.

- **`VECTOR_MEMORY_SIZE`**

  Syntax: `vector_memory_size = [ON | OFF]` (default `ON`)

  The initialization parameter `VECTOR_MEMORY_SIZE` specifies either the current size of the Vector Pool (at CDB level) or the maximum Vector Pool usage allowed by a PDB (at PDB level). The possible For more information about this parameter, see Size the Vector Pool.

- **`VECTOR_INDEX_NEIGHBOR_GRAPH_RELOAD`**

  Syntax: `vector_index_neighbor_graph_reload = [RESTART | OFF]` (default `OFF`)

  The initialization parameter `VECTOR_INDEX_NEIGHBOR_GRAPH_RELOAD` automatically loads HNSW indexes one by one after instance restart through a background task. For more information about this parameter, see Guidelines for Using Vector Indexes.

- **`VECTOR_QUERY_CAPTURE`**

  Syntax: `vector_query_capture = [ON | OFF]` (default `ON`)

  The initialization parameter `VECTOR_QUERY_CAPTURE` is used to enable and disable capture of query vectors. For more information about this parameter and about capturing query vectors, see Index Accuracy Report.

11 Vector Search PL/SQL APIs

Explore Oracle AI Vector Search APIs and reference materials.

- Oracle AI Vector Search PL/SQL Packages
  These are a set of PL/SQL packages related to Oracle AI Vector Search.

Oracle AI Vector Search PL/SQL Packages

These are a set of PL/SQL packages related to Oracle AI Vector Search.

For detailed information, see the following sections in *Oracle Database PL/SQL Packages and Types Reference*:

- DBMS_VECTOR

  The `DBMS_VECTOR` package simplifies common operations with Oracle AI Vector Search, such as extracting chunks or embeddings from user data, generating text for a given prompt, or creating vector indexes.
- DBMS_VECTOR_CHAIN

  The `DBMS_VECTOR_CHAIN` package enables advanced operations with Oracle AI Vector Search, such as chunking and embedding data along with text generation and summarization capabilities. It is more suitable for text processing with similarity search, using functionality that can be pipelined together for an end-to-end search.