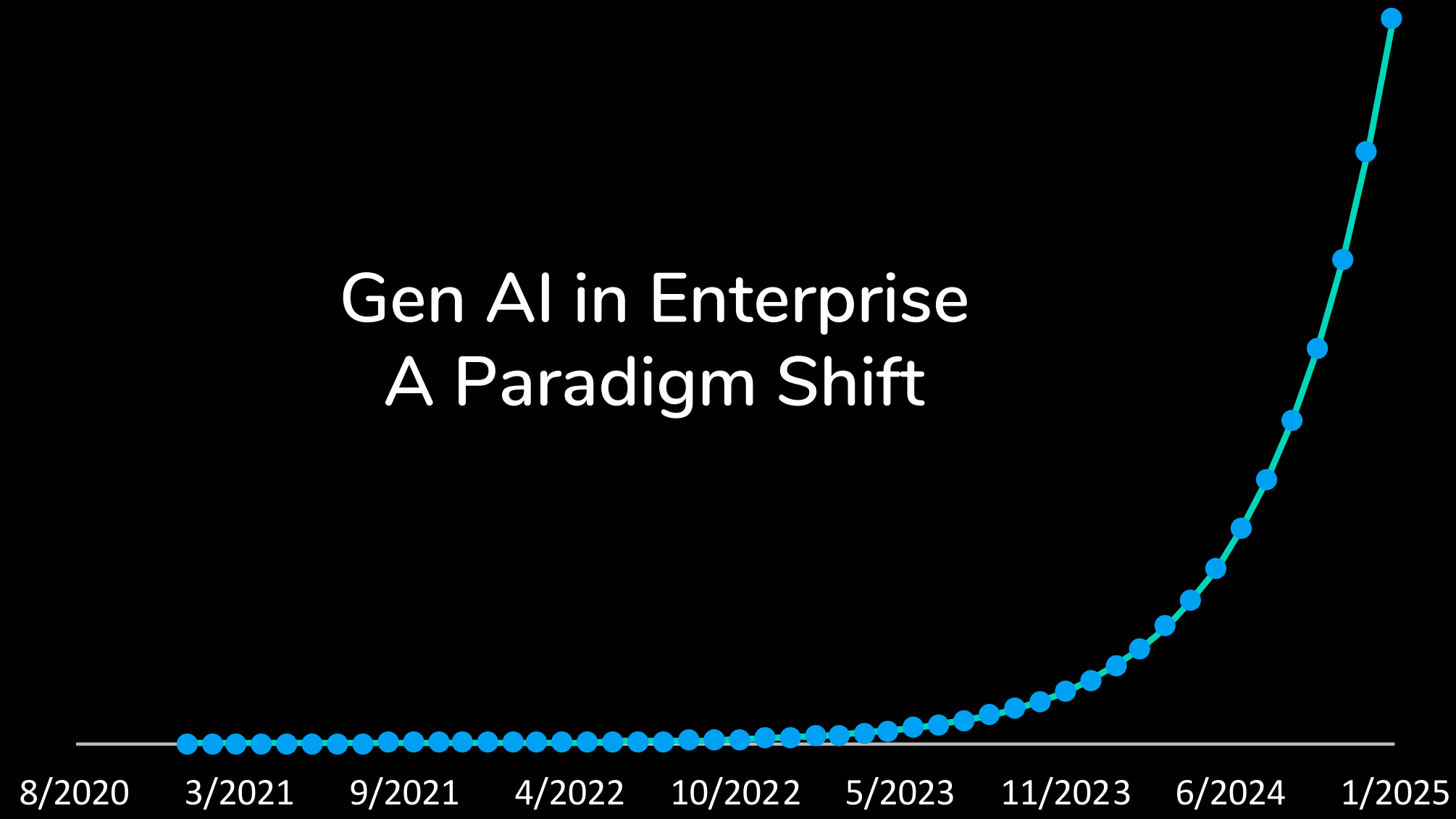
Gen AI in Enterprise
A Paradigm Shift

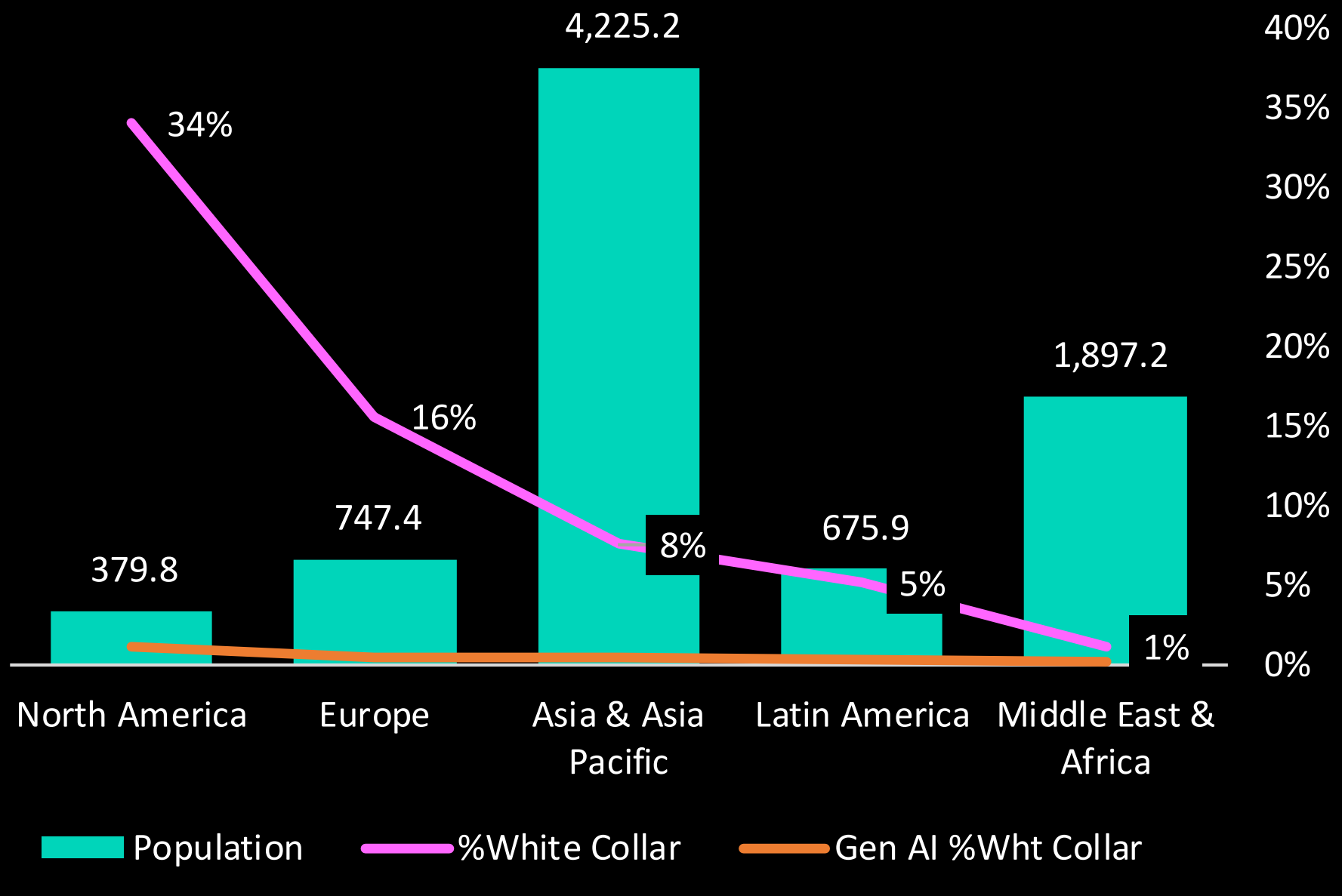


What We’ll Cover

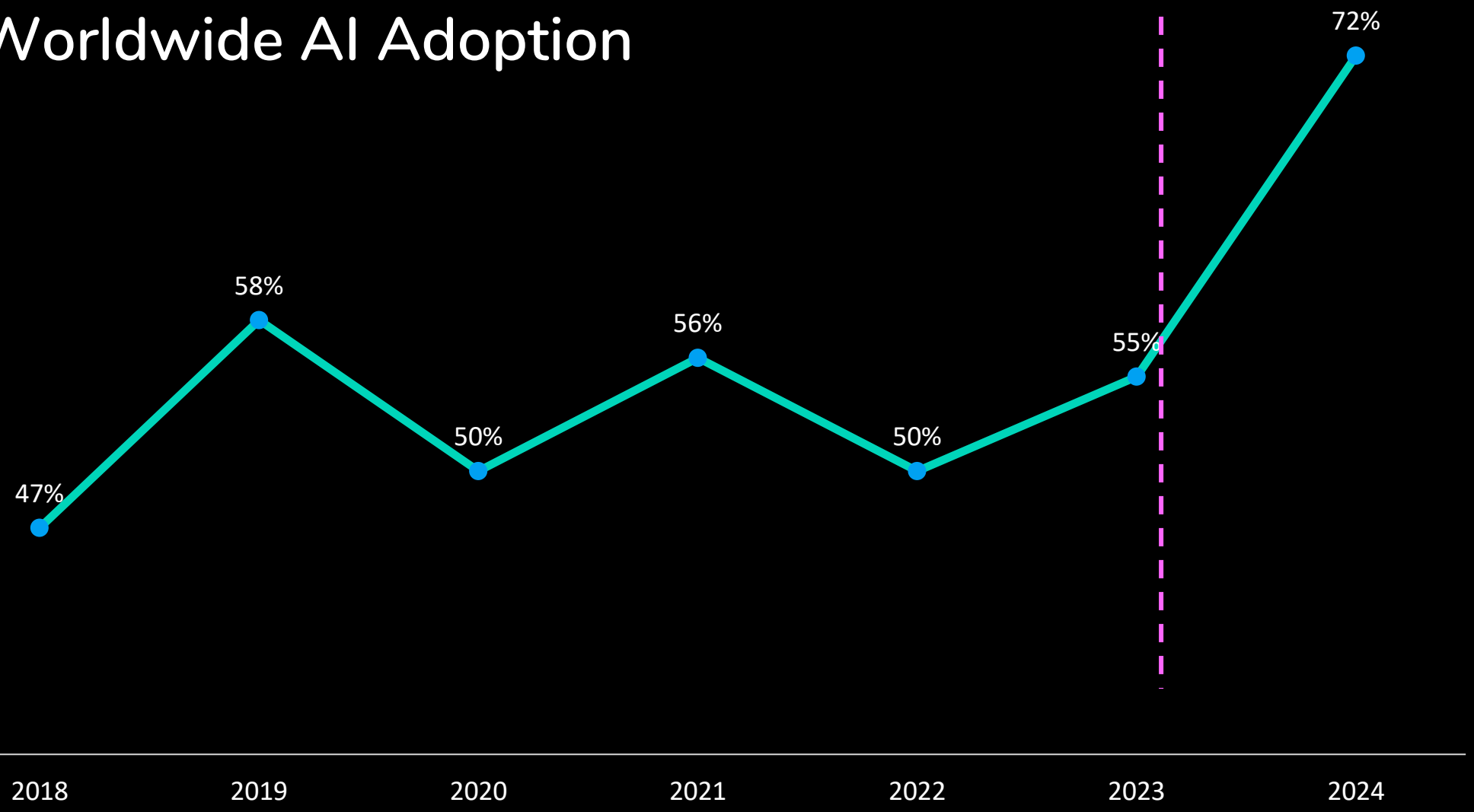
1. Trends & Adoption
2. Build vs Buy
3. Open Source
4. Gen AI Design for Enterprise
5. Case Study Examples

1. Trends & Adoption
2. Build vs Buy
3. Open Source
4. Gen AI Design for Enterprise
5. Case Study Examples

		Millions	
Region	Population	White Collar	Gen AI Corp Users
North America	379.8	129.3	1.5
Europe	747.4	116.9	0.6
Asia & Asia Pacific	4,225.2	321.2	1.7
Latin America	675.9	35.0	0.1
Middle East & Africa	1,897.2	22.6	0.0
Total	7,925.4	625.1	3.8

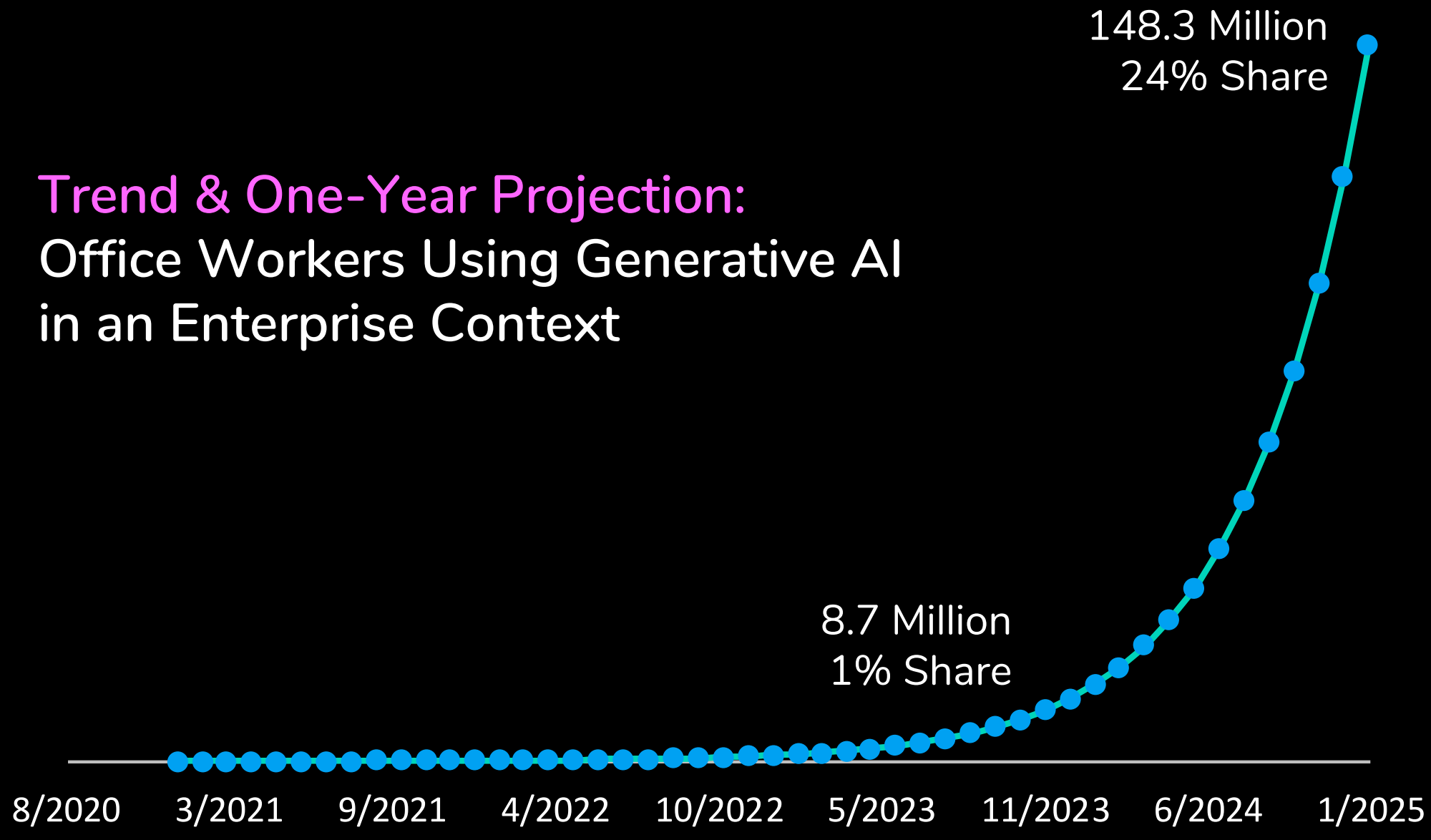

4,225.2
1,897.2
747.4
675.9
379.8
34%
16%
8%
5%
1%
40%
35%
30%
25%
20%
15%
10%
5%
0%
North America
Europe
Asia & Asia Pacific
Latin America
Middle East & Africa
Population
%White Collar
Gen AI %Wht Collar

Worldwide AI Adoption



Source: McKinsey, The State of AI (Early 2024)
https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

Trend & One-Year Projection:
Office Workers Using Generative AI in an Enterprise Context



1. Trends & Adoption
2. Build vs Buy
3. Open Source
4. Gen AI Design for Enterprise
5. Case Study Examples

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Up next

Celia Wanderley: AI Innovator of the Year

AI Master Group

Celia is the Chief Innovation Officer at Bits In Glass (BIG), a top Canadian IT consulting firm. Prior to that, she held senior leadership roles at AltaML and at Deloitte Canada. Celia was recognized as the AI Innovator of th...

Oct 12 • 30 min 54 sec

About

Hosted by Jim Griffin, this show features the researchers and leaders who are building the future of AI in their work today. Join us for thought-provoking conversations about the evolving world of artificial intelligence.

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Jodi Blomberg
VP Data Science
Cox Automotive

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Jodi Blomberg
VP Data Science
Cox Automotive

Build if . . .

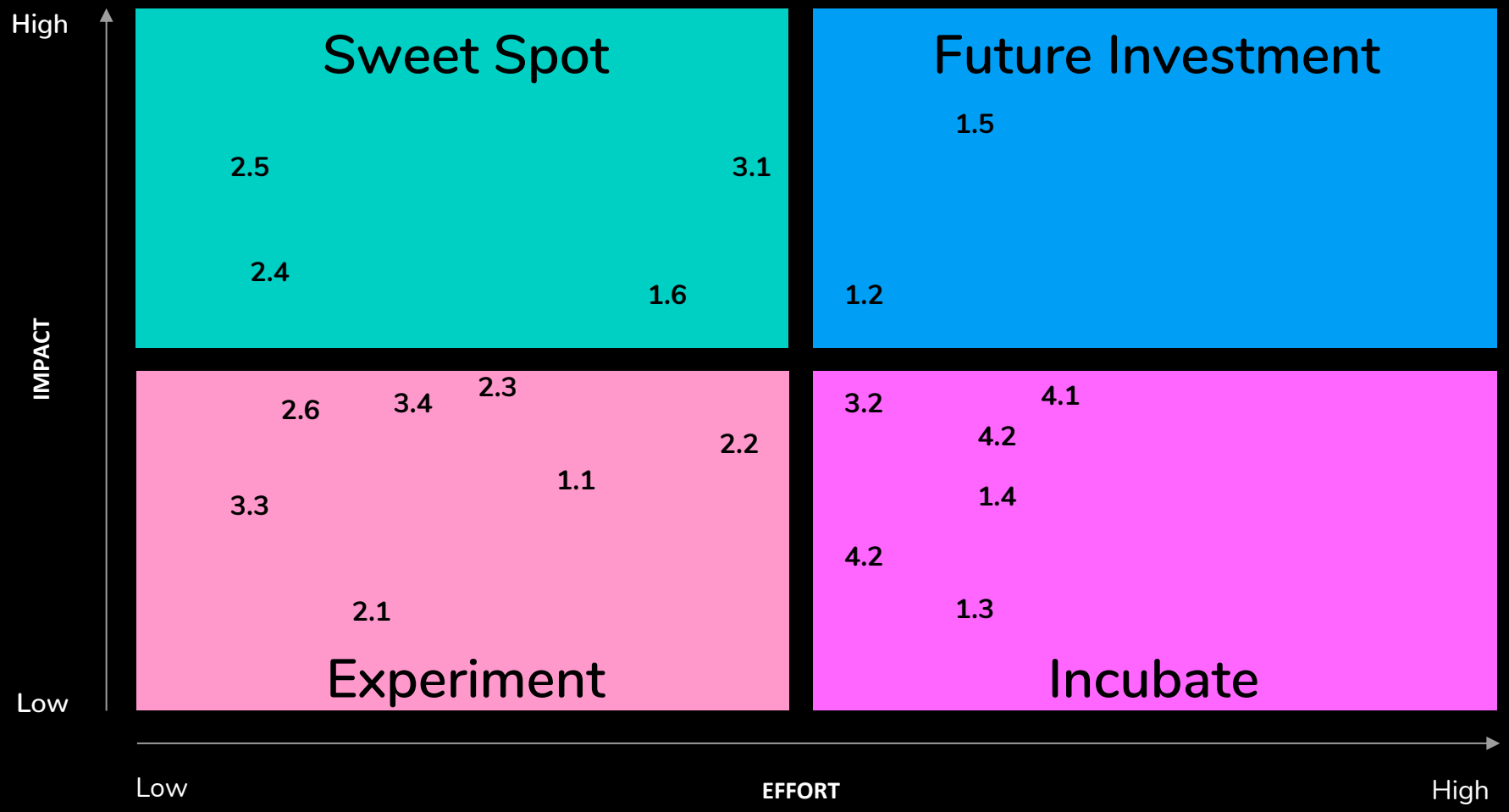
- Proprietary Data
- Multiple sources
- Revenue Trumps Efficiency

Jodi Blomberg
VP Data Science
Cox Automotive

Diversified Portfolio

- Core Projects ROI Baseline
- Strategic Bets
- Moonshots (4-6 Weeks)

A Framework



HYPOTHETICAL SCENARIO

AI Use Cases for an Energy company, segmented by target initiative:

1. **Productivity**
   1. Flow Rate Prediction
   2. Downhole Pressure Optimization
   3. Breccia Image Classification
   4. Mean Grain Size Estimation
   5. Well Segmentation
   6. Demand Visibility Prediction
2. **Efficiency**
   1. Equipment Wear & Tear
   2. Predictive Maintenance
   3. Optimal Pump Down
   4. P&ID Drawing Extraction
   5. Instrumentation Issue Detection
   6. Material Master Search
3. **Safety**
   1. CV Enabled Asset Management
   2. Wellhole Prediction
   3. Structure Detection Identification
   4. Cable Tension Modeling
4. **Environment**
   1. Smart Power Notification
   2. Mine Aquifer Seepage
   3. Pipeline Integrity

1. Trends & Adoption
2. Build vs Buy
3. Open Source
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Computer Science > Computation and Language

[Submitted on 12 Jun 2017 (v1), last revised 2 Aug 2023 (this version, v7)]

Attention Is All You Need

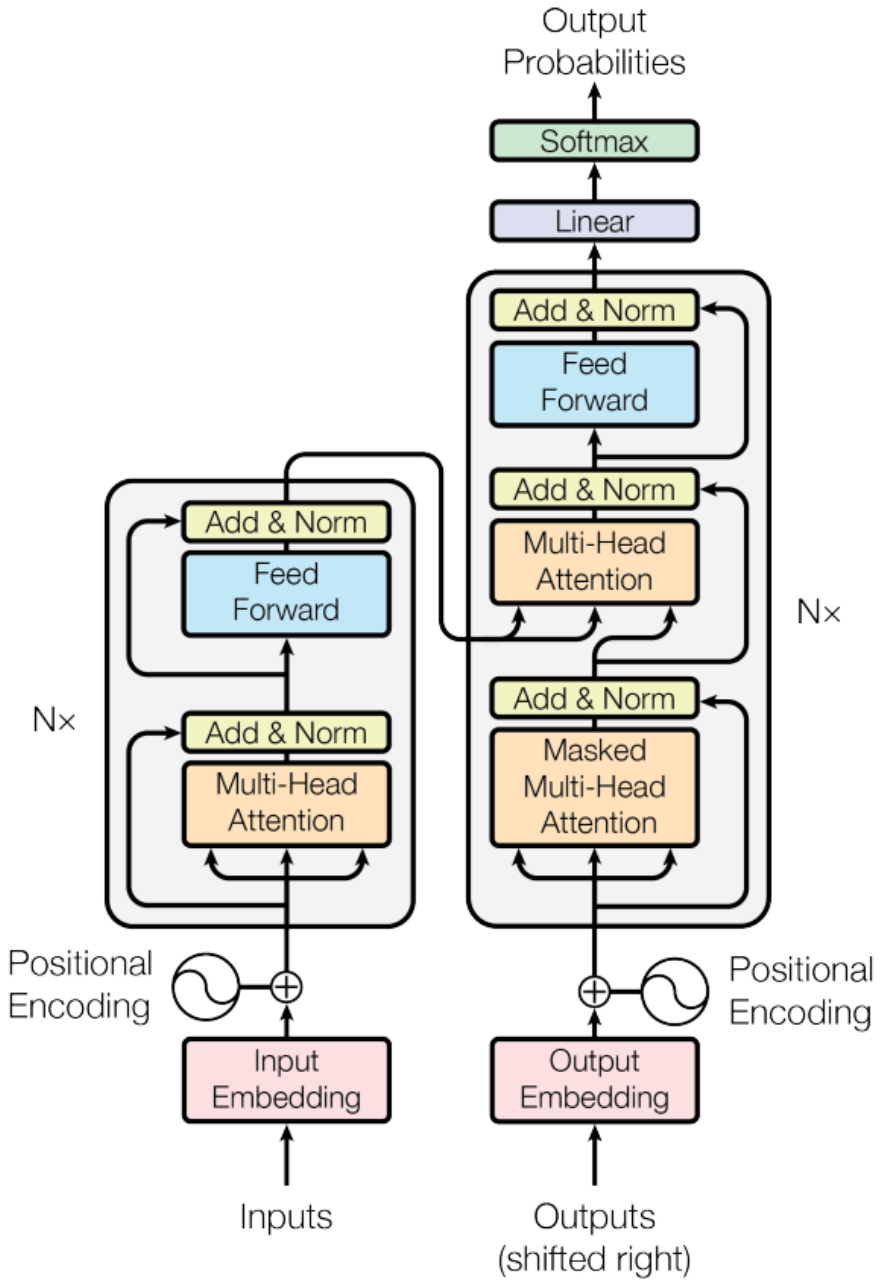
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, Illia Polosukhin

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder-decoder configuration. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Comments: 15 pages, 5 figures
Subjects: **Computation and Language (cs.CL)**; Machine Learning (cs.LG)
Cite as: arXiv:1706.03762 **[cs.CL]**
(or arXiv:1706.03762v7 **[cs.CL]** for this version)
https://doi.org/10.48550/arXiv.1706.03762

Submission history

From: Llion Jones [view email]
[v1] Mon, 12 Jun 2017 17:57:34 UTC (1,102 KB)
[v2] Mon, 19 Jun 2017 16:49:45 UTC (1,125 KB)
[v3] Tue, 20 Jun 2017 05:20:02 UTC (1,125 KB)
[v4] Fri, 30 Jun 2017 17:29:30 UTC (1,124 KB)
[v5] Wed, 6 Dec 2017 03:30:32 UTC (1,124 KB)
[v6] Mon, 24 Jul 2023 00:48:54 UTC (1,124 KB)
[v7] Wed, 2 Aug 2023 00:41:18 UTC (1,124 KB)


Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding
Inputs
Outputs (shifted right)

SBERT.net
Sentence Transformers
Star 15,038
Search docs

GETTING STARTED
Installation
Quickstart

SENTENCE TRANSFORMER
⊞ Usage
⊞ Pretrained Models
⊞ Training Overview
⊞ Dataset Overview
⊞ Loss Overview
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CROSS ENCODER
⊞ Usage
⊞ Pretrained Models
Training Overview
⊞ Training Examples

PACKAGE REFERENCE

Tip

Sentence Transformers v3.2 just released, introducing the ONNX and OpenVINO backends for Sentence Transformer models. Read SentenceTransformer > Usage > Speeding up Inference to learn more about the new backends and what they can mean for your inference speed.

SentenceTransformers Documentation

Sentence Transformers (a.k.a. SBERT) is the go-to Python module for accessing, using, and training state-of-the-art text and image embedding models. It can be used to compute embeddings using Sentence Transformer models (quickstart) or to calculate similarity scores using Cross-Encoder models (quickstart). This unlocks a wide range of applications, including semantic search, semantic textual similarity, and paraphrase mining.

A wide selection of over 5,000 pre-trained Sentence Transformers models are available for immediate use on 🤗 Hugging Face, including many of the state-of-the-art models from the Massive Text Embeddings Benchmark (MTEB) leaderboard. Additionally, it is easy to train or finetune your own models using Sentence Transformers, enabling you to create custom models for your specific use cases.

Sentence Transformers was created by UKPLab and is being maintained by 🤗 Hugging Face. Don't hesitate to open an issue on the Sentence Transformers repository if something is broken or if you have further questions.

Usage

See also

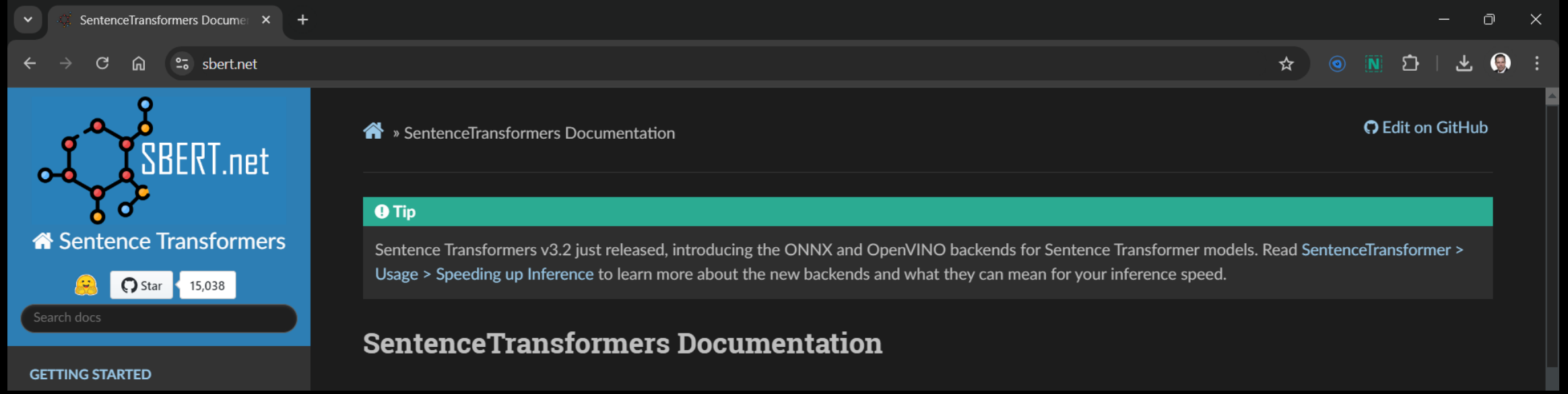
See the Quickstart for more quick information on how to use Sentence Transformers.

Using Sentence Transformer models is elementary:

```
from sentence_transformers import SentenceTransformer

# 1. Load a pretrained Sentence Transformer model
```

Installation



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huggingface.co/models

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- Any-to-Any

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- Image Segmentation
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- Image-to-Text
- Image-to-Image
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- Video Classification
- Text-to-Video
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- Mask Generation
- Zero-Shot Object Detection
- Text-to-3D
- Image-to-3D
- Image Feature Extraction
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Natural Language Processing

- Text Classification
- Token Classification
- Table Question Answering
- Question Answering
- Zero-Shot Classification
- Translation

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- jxm/cde-small-v1
  Feature Extraction • Updated 4 days ago • 2.82k • ♡ 219
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  Text Generation • Updated 13 days ago • 258k • ♡ 469
- stepfun-ai/GOT-OCR2_0
  Image-Text-to-Text • Updated 26 days ago • 208k • ♡ 1.03k
- black-forest-labs/FLUX.1-schnell
  Text-to-Image • Updated Aug 16 • 1.05M • ♡ 2.57k
- meta-llama/Llama-3.2-11B-Vision-Instruct
  Image-Text-to-Text • Updated 14 days ago • 733k • ♡ 634
- arcee-ai/SuperNova-Medius
  Text Generation • Updated 3 days ago • 945 • ♡ 79
- alimama-creative/FLUX.1-Turbo-Alpha
  Text-to-Image • Updated about 2 hours ago • 554 • ♡ 72
- meta-llama/Llama-3.1-8B-Instruct
  Text Generation • Updated 18 days ago • 2.71M • ♡ 2.77k
- meta-llama/Llama-3.2-3B-Instruct
- allenai/Molmo-7B-D-0924

https://huggingface.co/black-forest-labs/FLUX.1-dev

all-MiniLM-L6-v2

- Trained on over 1 billion samples
- State-of-the-art sentence embeddings (x384)
- Has 6 transformer encoder layers
- A small model
- Mimics performance of large BERT model
- Use-cases: Text classification, sentiment analysis, semantic search

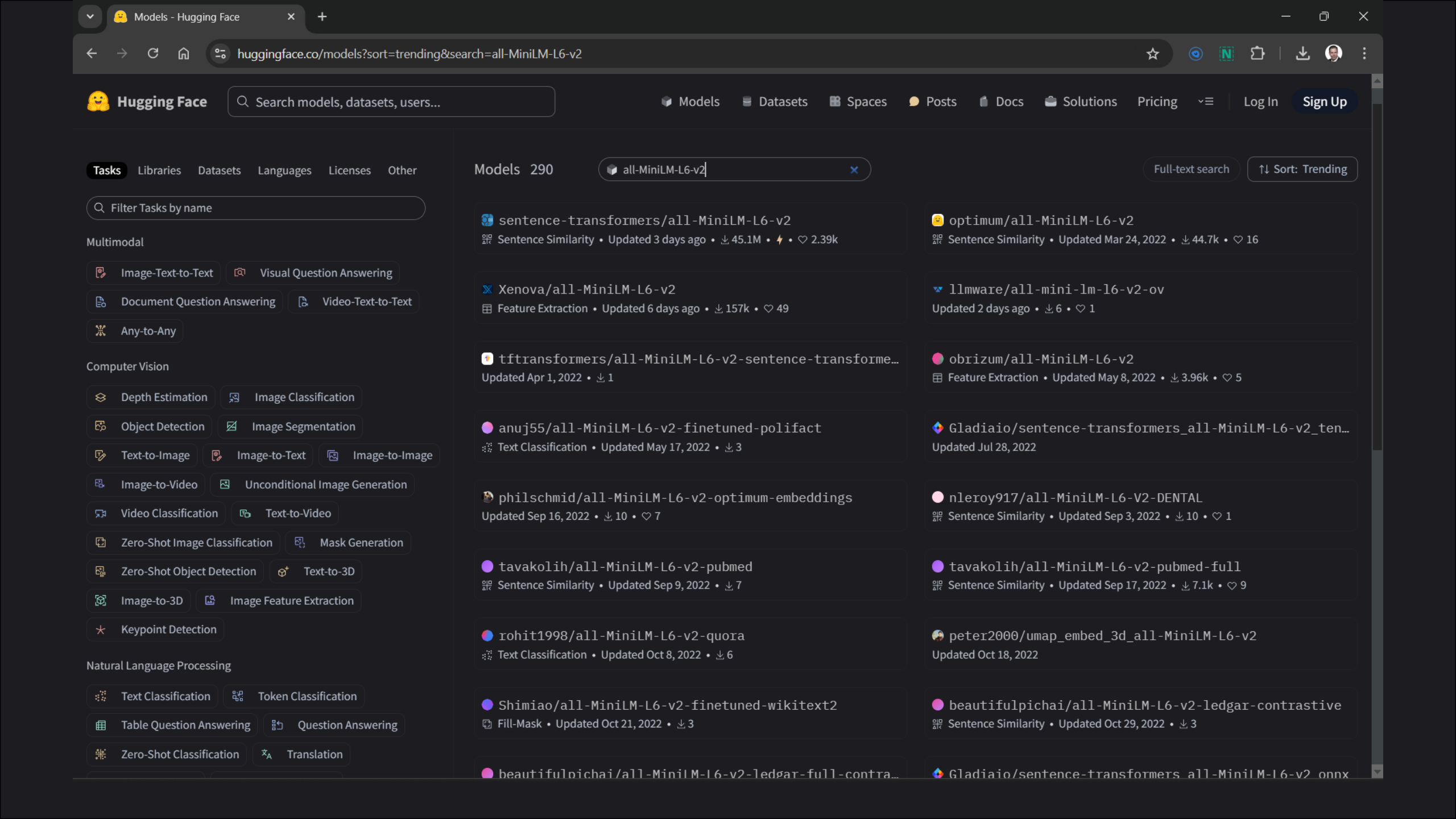
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Image Segmentation
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Image-to-Text
Image-to-Image
Image-to-Video
Unconditional Image Generation
Video Classification
Text-to-Video
Zero-Shot Image Classification
Mask Generation
Zero-Shot Object Detection
Text-to-3D
Image-to-3D
Image Feature Extraction
Keypoint Detection
Natural Language Processing
Text Classification
Token Classification
Table Question Answering
Question Answering
Zero-Shot Classification
Translation
Models 290
all-MiniLM-L6-v2
Full-text search
Sort: Trending
sentence-transformers/all-MiniLM-L6-v2
Sentence Similarity • Updated 3 days ago • 45.1M • 2.39k
optimum/all-MiniLM-L6-v2
Sentence Similarity • Updated Mar 24, 2022 • 44.7k • 16
Xenova/all-MiniLM-L6-v2
Feature Extraction • Updated 6 days ago • 157k • 49
llmware/all-mini-lm-l6-v2-ov
Updated 2 days ago • 6 • 1
tftransformers/all-MiniLM-L6-v2-sentence-transforme...
Updated Apr 1, 2022 • 1
obrizum/all-MiniLM-L6-v2
Feature Extraction • Updated May 8, 2022 • 3.96k • 5
anuj55/all-MiniLM-L6-v2-finetuned-polifact
Text Classification • Updated May 17, 2022 • 3
Gladiaio/sentence-transformers_all-MiniLM-L6-v2_ten...
Updated Jul 28, 2022
philschmid/all-MiniLM-L6-v2-optimum-embeddings
Updated Sep 16, 2022 • 10 • 7
nleroy917/all-MiniLM-L6-V2-DENTAL
Sentence Similarity • Updated Sep 3, 2022 • 10 • 1
tavakolih/all-MiniLM-L6-v2-pubmed
Sentence Similarity • Updated Sep 9, 2022 • 7
tavakolih/all-MiniLM-L6-v2-pubmed-full
Sentence Similarity • Updated Sep 17, 2022 • 7.1k • 9
rohit1998/all-MiniLM-L6-v2-quora
Text Classification • Updated Oct 8, 2022 • 6
peter2000/umap_embed_3d_all-MiniLM-L6-v2
Updated Oct 18, 2022
Shimiao/all-MiniLM-L6-v2-finetuned-wikitext2
Fill-Mask • Updated Oct 21, 2022 • 3
beautifulpichai/all-MiniLM-L6-v2-ledgar-contrastive
Sentence Similarity • Updated Oct 29, 2022 • 3
beautifulpichai/all-MiniLM-L6-v2-ledgar-full-contra...
Gladiaio/sentence-transformers_all-MiniLM-L6-v2_onnx

NLP7_CategorizeNewsArticles_

colab.research.google.com/drive/14YLCDmKAzeGSV_TzZCFh2FMcp80dF4hW#scrollTo=svwbW6qDUB_B

NLP7_CategorizeNewsArticles_CaseStudy.ipynb

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Connect T4 Gemini

```
[ ]
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 86.0/86.0 kB 1.8 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 11.0 MB/s eta 0:00:00
  Building wheel for sentence-transformers (setup.py) ... done
```

```
# to read and manipulate the data
import pandas as pd
import numpy as np
pd.set_option('max_colwidth', None)    # setting column to the maximum column width as per the data

# to visualise data
import matplotlib.pyplot as plt
import seaborn as sns

# to compute distances
from scipy.spatial.distance import cdist, pdist
from sklearn.metrics import silhouette_score

# importing the PyTorch Deep Learning library
import torch

# to import the model
from sentence_transformers import SentenceTransformer

# to cluster the data
from sklearn.cluster import KMeans

# to compute metrics
from sklearn.metrics import classification_report

# to avoid displaying unnecessary warnings
import warnings
warnings.filterwarnings("ignore")
```

Loading the dataset

NLP7_CategorizeNewsArticles_(

colab.research.google.com/drive/14YLCDmKAzeGSV_TzZCFh2FMcp80dF4hW#scrollTo=yNDAvKn0Klwa

NLP7_CategorizeNewsArticles_CaseStudy.ipynb

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Connect T4 Gemini

```
#Defining the model
model = SentenceTransformer('sentence-transformers/all-MiniLM-L6-v2')
```

.gitattributes: 100% 1.18k/1.18k [00:00<00:00, 83.4kB/s]

1_Pooling/config.json: 100% 190/190 [00:00<00:00, 11.5kB/s]

README.md: 100% 10.6k/10.6k [00:00<00:00, 660kB/s]

config.json: 100% 612/612 [00:00<00:00, 49.0kB/s]

config_sentence_transformers.json: 100% 116/116 [00:00<00:00, 9.65kB/s]

data_config.json: 100% 39.3k/39.3k [00:00<00:00, 2.74MB/s]

pytorch_model.bin: 100% 90.9M/90.9M [00:00<00:00, 253MB/s]

sentence_bert_config.json: 100% 53.0/53.0 [00:00<00:00, 3.09kB/s]

special_tokens_map.json: 100% 112/112 [00:00<00:00, 9.66kB/s]

tokenizer.json: 100% 466k/466k [00:00<00:00, 2.42MB/s]

tokenizer_config.json: 100% 350/350 [00:00<00:00, 27.5kB/s]

train_script.py: 100% 13.2k/13.2k [00:00<00:00, 937kB/s]

vocab.txt: 100% 232k/232k [00:00<00:00, 9.17MB/s]

modules.json: 100% 349/349 [00:00<00:00, 15.4kB/s]

Encoding the dataset

[ ] 6 cells hidden

Semantic Search

NLP7_CategorizeNewsArticles_(

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NLP7_CategorizeNewsArticles_CaseStudy.ipynb

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Connect T4 Gemini

```
[ ] # defining a function to find the top k similar sentences for a given query
    def top_k_similar_sentences(embedding_matrix, query_text, k):
        # encoding the query text
        query_embedding = model.encode(query_text)

        # calculating the cosine similarity between the query vector and all other encoded vectors of our dataset
        score_vector = np.dot(embedding_matrix,query_embedding)

        # sorting the scores in descending order and choosing the first k
        top_k_indices = np.argsort(score_vector)[::-1][:k]

        # returning the corresponding reviews
        return data.loc[list(top_k_indices), 'Text']
```

```
# defining the query text
query_text = "Budget for elections"

# displaying the top 5 similar sentences
top_k_reviews = top_k_similar_sentences(embedding_matrix, query_text, 5)

for i in top_k_reviews:
    print(i, end="\n\n")
```

```
'Debate needed' on donations cap

A cap on donations to political parties should not be introduced yet, the elections watchdog has said.

Fears that big donors can buy political favours have sparked calls for a limit. In a new report, the Electoral Commission says it is worth debating a Â£10,000 cap for the future bu

There were almost Â£68m in reported donations to political parties in 2001, 2002 and 2003, with nearly Â£12m of them from individual gifts worth more than Â£1m. The rules have alre

Even without changes the commission does urge political parties to seek out more small-scale donations and suggests there should be income tax relief for gifts under Â£200. It also

The report suggests doubling the money which can be spent by candidates, while cutting national spending limits from Â£20m to Â£15m. The commission also says the spending limits fo
```

NLP7_CategorizeNewsArticles_

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NLP7_CategorizeNewsArticles_CaseStudy.ipynb

File Edit View Insert Runtime Tools Help Last saved at October 12

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+ Code + Text

Connect T4 Gemini

```
[ ] # defining the query text
    query_text = "High imports and exports"

    # displaying the top 5 similar sentences
    top_k_reviews = top_k_similar_sentences(embedding_matrix, query_text, 5)

    for i in top_k_reviews:
        print(i, end="\n\n")
```

```
US trade gap ballooned in October

The US trade deficit widened by more than expected in October, hitting record levels after higher oil prices raised import costs, figures have shown

The trade shortfall was $55.5bn (Â£29bn), up 9% from September, the Commerce Department said. That pushed the 10 month deficit to $500.5bn. Imports rose by 3.4%, while exports increas

Despite this optimism, significant concerns remain as to how the US will fund its trade and budget deficits should they continue to widen. Another problem highlighted by analysts was

Trade gap narrows as exports rise

The UK's trade gap narrowed in November, helped by a 7.5% rise in exports outside the European Union.

According to the Office for National Statistics, the difference between what the UK exported and imported was Â£3.1bn ($5.8bn), down from October's Â£3.6bn. Overall UK exports - inclu

November saw an improvement in export levels to both the European Union and the rest of the world, the Office for National Statistics (ONS) said. EU exports rose 2%, fuelled by an inc

The UK's deficit with the EU fell to Â£1.9bn from Â£2.1bn, while its non-EU shortfall dropped to Â£2.7bn from Â£2.9bn in October.

The country's surplus on trade-in-services remained steady at Â£1.5bn for the fifth month in a row. Paul Dales, UK economist for Capital Economics, said the figures represented an imp

US trade gap hits record in 2004

The gap between US exports and imports hit an all-time high of $671.7bn (Â£484bn) in 2004, latest figures show.

The Commerce Department said the trade deficit for all of last year was 24.4% above the previous record - 2003's imbalance of $496.5bn. The deficit with China, up 30.5% at $162bn, was

Democrats claim the administration has not done enough to clamp down on unfair foreign trade practices. For example, they believe China's currency policy - which US manufacturers clai
```

Comparing with Actual Categories

```
[ ] # loading the actual labels
    labels = pd.read_csv("/content/drive/news_article_labels.csv")
```

```
[ ] labels.shape
```

```
(2127, 1)
```

```
[ ] # checking the unique labels
    labels['Label'].unique()
```

```
array(['Politics', 'Sports', 'Technology', 'Entertainment', 'Business'],
      dtype=object)
```

```
[ ] # adding the actual categories to our dataframe
    clustered_data['Actual Category'] = labels['Label'].values
```

```
print(classification_report(clustered_data['Actual Category'], clustered_data['Category']))
```

```
                precision    recall  f1-score   support

      Business       0.96      0.93      0.95       503
 Entertainment       0.96      0.95      0.95       369
      Politics       0.96      0.95      0.95       403
        Sports       0.98      0.99      0.99       505
    Technology       0.91      0.97      0.93       347

      accuracy                           0.96      2127
     macro avg       0.95      0.96      0.96      2127
  weighted avg       0.96      0.96      0.96      2127
```

1. Trends & Adoption
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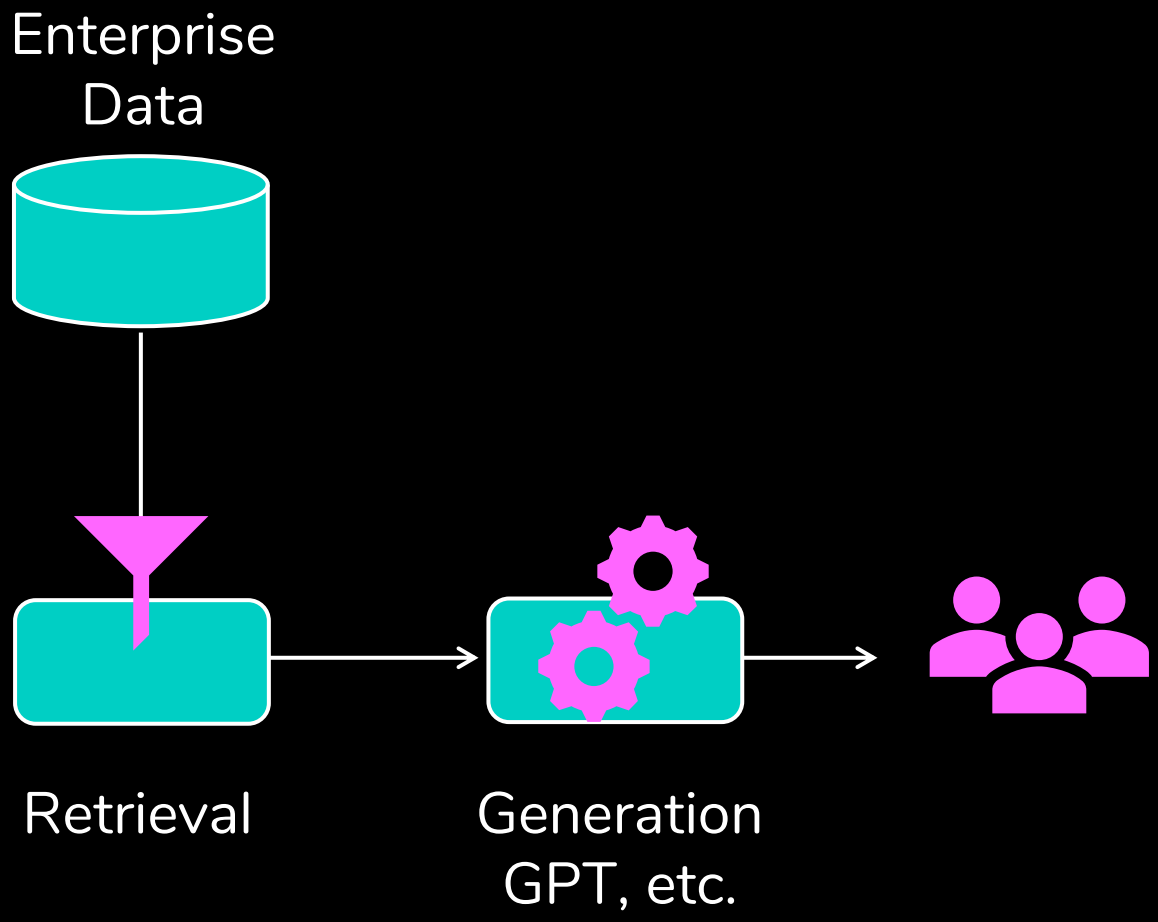
5. Case Study Examples

Enterprise Context

Retrieval Augmented Generation (RAG)

- Combine the strengths of retrieval and generative models.
- More coherent and contextually-relevant responses.

- Enterprise Context



Knowledge Graph

A way to organize and connect information in a meaningful manner.

- Entities (people, places, events)
- Properties
- Relationships

Database

Enables similarity-based retrieval.

RAG can leverage this to retrieve similar documents or knowledge from your database, contributing to more informed and contextually relevant generation.

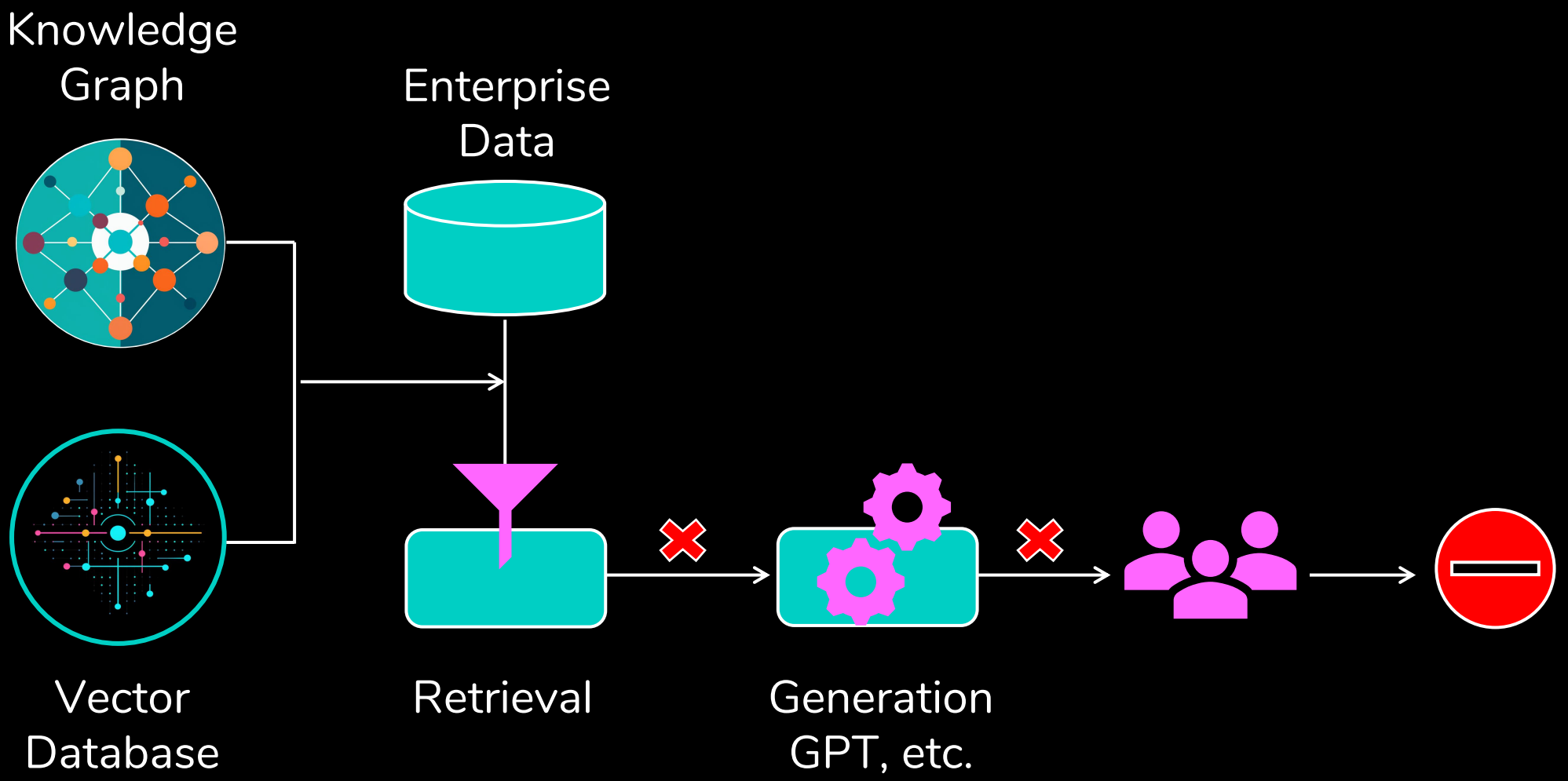
Database

- Apache Airflow
- Apache NiFi
- Talend
- Dataiki DSS
- Data Factory (Azure)
- Glue (aws)

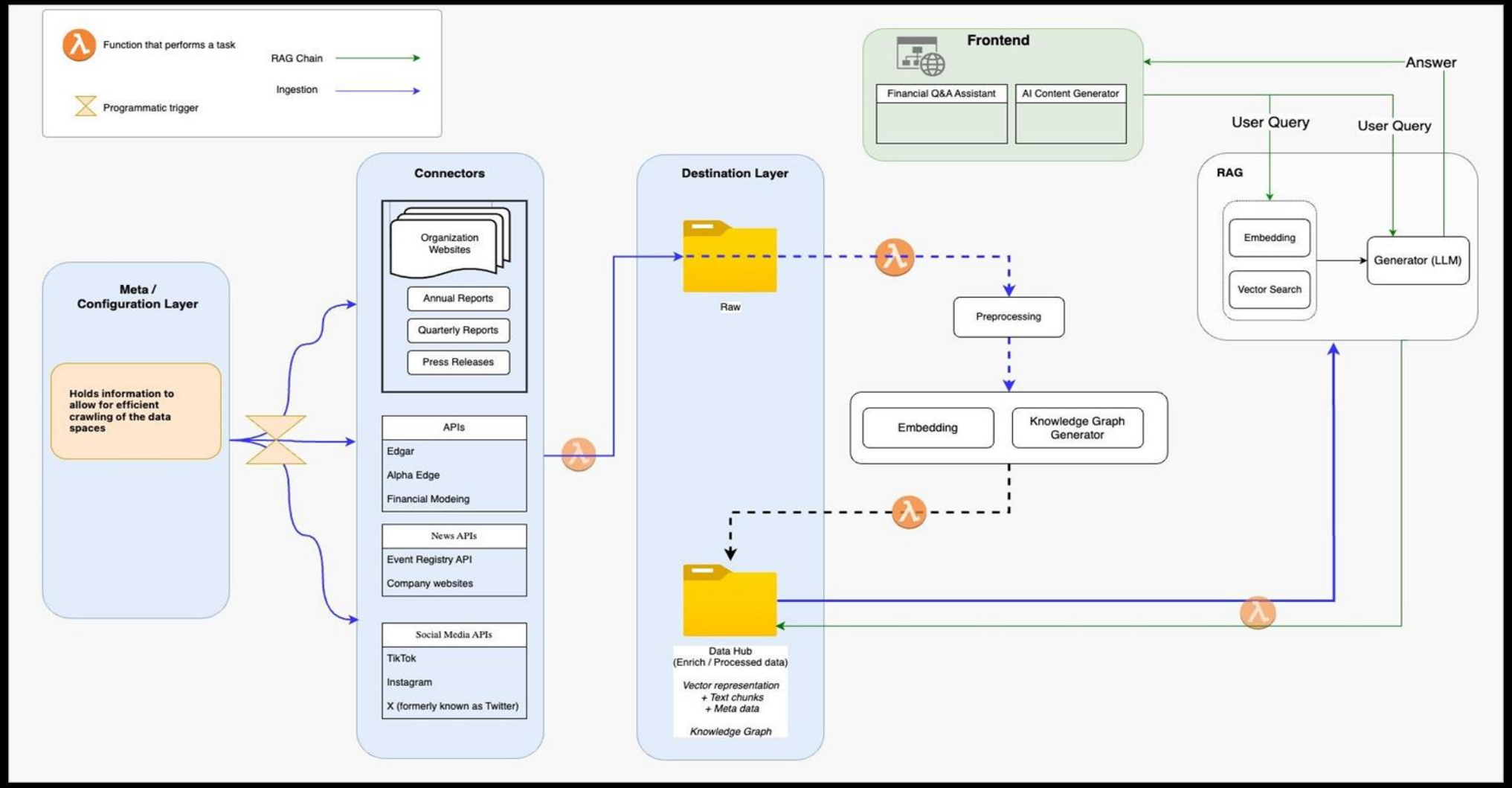
Data Security

- Private Environment. Customization
- Data Isolation & Encryption
- Access Control. Audit Trails. Monitoring
- Redaction and Anonymization
- Training Data Review

Full Enterprise Context



Sample Architecture



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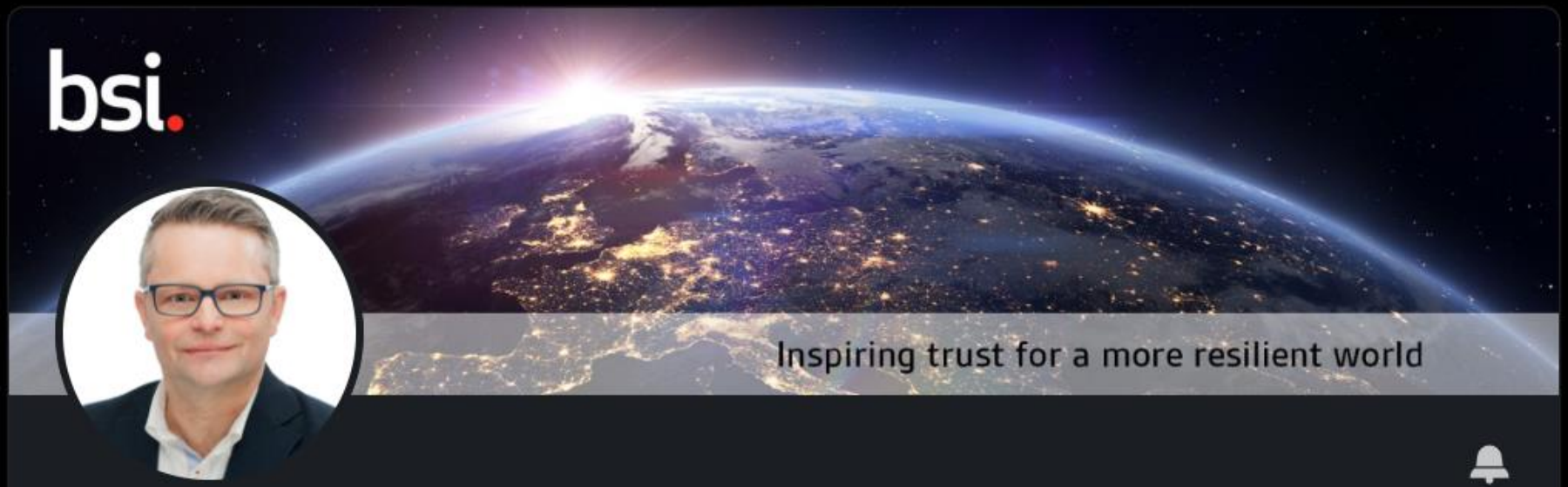

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About

Scientific researcher with a background in biology, marine conservation, and environmental policy. My interests include ecosystem services approaches, global marine policy, conservation project management, and urban sustainability. I have experience working across scales, from local to international, on topics ranging from marine protected areas to natural capital assessments/approaches to the intersections of nature and health. I also have demonstrated technical e ...see more


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University of Arizona

Jim Griffin

Explore research activities

Search for experts, explore research areas, and find collaborations at the University of Arizona using our Knowledge Map (KMAP).

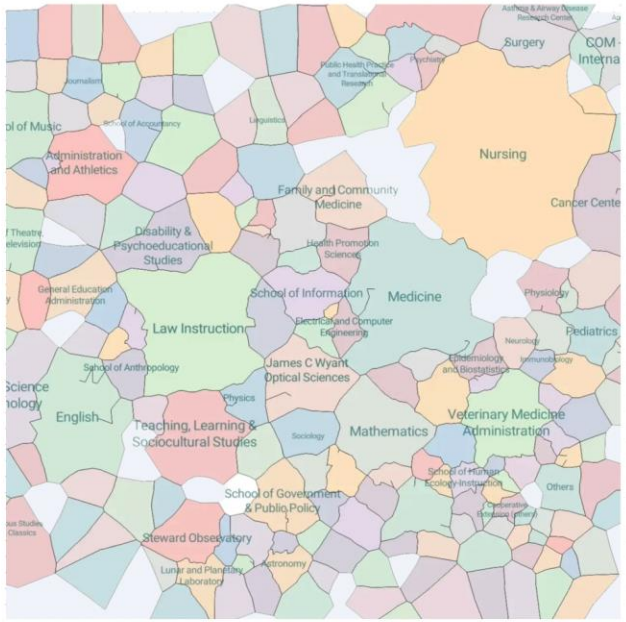
GO TO MAP

See how to explore the university research map

Ask question

ASK KMAP

Get information about the university from our generative AI



Research at a glance

Statistics derived from only the **active researchers** within the university

RESEARCHERS	CONNECTIONS	DEPARTMENTS	GRANTS	CITATIONS
6056	25.6K	252	23K	6.5M
Active researchers in KMap	Internal connections between researchers	Departments in KMap	Grants for active and completed projects in KMap	Research citations

- Voice-activated workflows
- Semantic search, text classification
- Code assistant
- MLOps
- Computer Vision
- Knowledge Map

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