HAYSTACK
The Search Relevance Conference

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Personalizing search using multimodal latent behavioral embeddings

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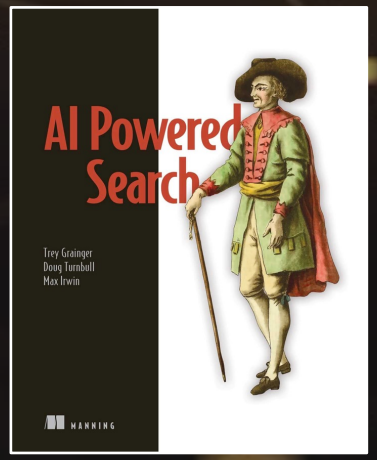


#haystackconf

Searchkernel

Building the next generation of Search.

Career

Searchkernel

Founder / CTO

Presearch

Chief Technology Officer

Lucidworks

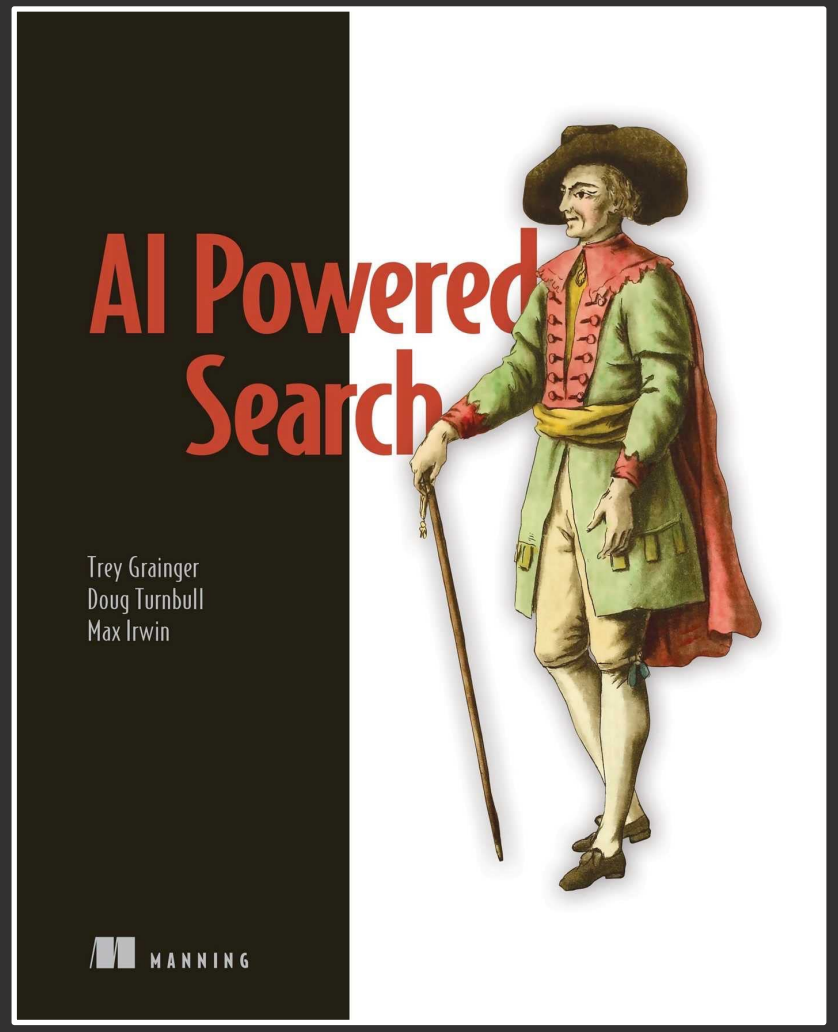
Chief Algorithms Officer
SVP Engineering

CAREERBUILDER™

Director of Engineering, Search & Recommendations

Books

Education



AI-Powered Search

- RAG (Retrieval Augmented Generation)
- Generative Search & Summarization
- Learning to Rank
- Semantic Search
- Dense Vector Search
- Fine-tuning LLMs for Search
- Personalized Search & Recommendations
- Knowledge Graph Learning
- User signals boosting & click models
- Crowdsourced Relevance

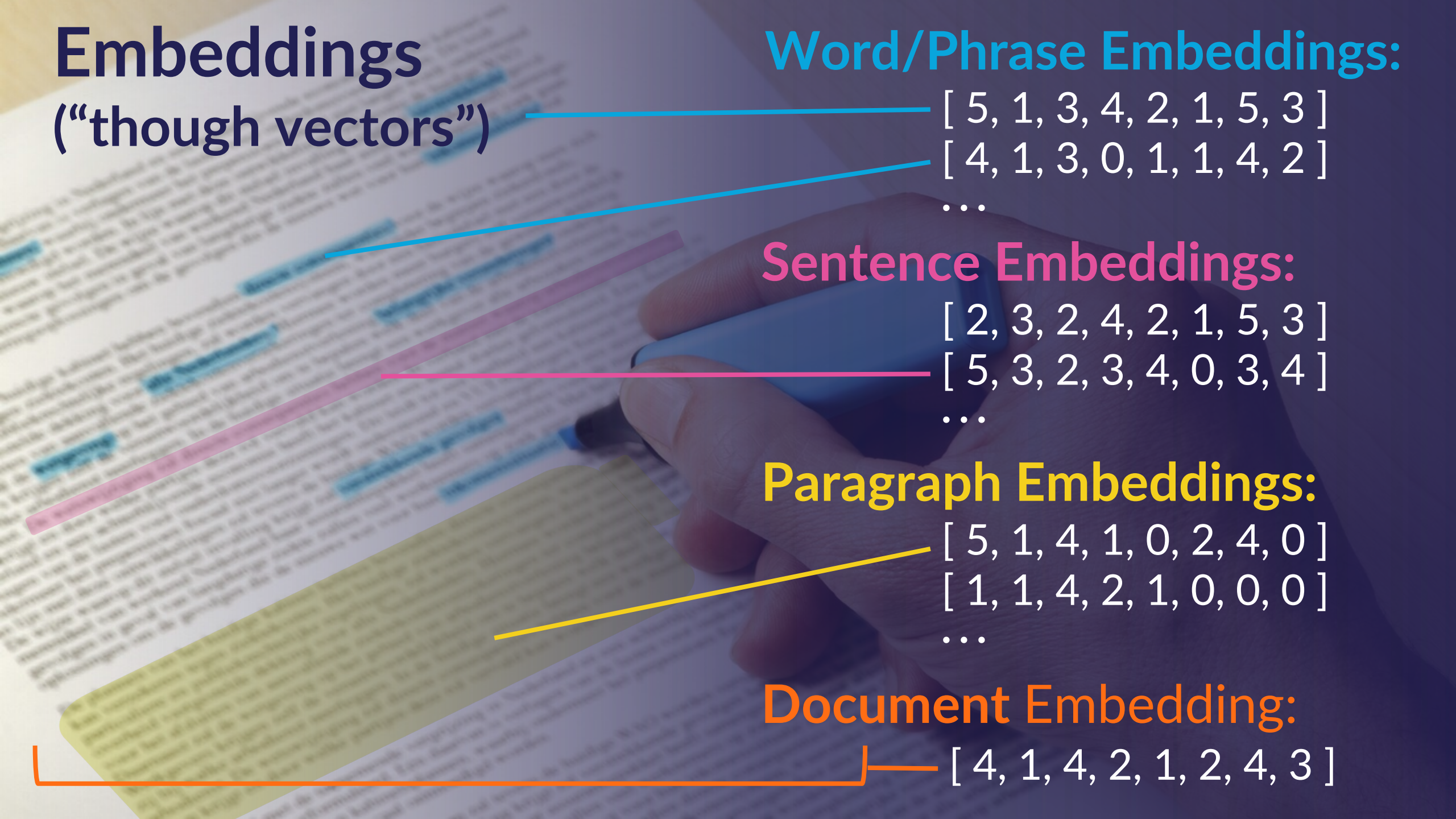
(45% Discount Code: **ctwhaystack45**)

https://aiPoweredSearch.*com*

Agenda

- The personalization spectrum between search and recommendations
- Leveraging a user's signals to implement collaborative filtering and personalization from latent features
- Using embedding vectors to generate personalization profiles
- Mixing user signals and content-based attributes to generate multimodal personalization
- Clustering products by embeddings to create personalization guardrails
- Avoiding the pitfalls of personalized search

What is an embedding?


Embeddings
("though vectors")
Word/Phrase Embeddings:
[5, 1, 3, 4, 2, 1, 5, 3]
[4, 1, 3, 0, 1, 1, 4, 2]
...
Sentence Embeddings:
[2, 3, 2, 4, 2, 1, 5, 3]
[5, 3, 2, 3, 4, 0, 3, 4]
...
Paragraph Embeddings:
[5, 1, 4, 1, 0, 2, 4, 0]
[1, 1, 4, 2, 1, 0, 0, 0]
...
Document Embedding:
[4, 1, 4, 2, 1, 2, 4, 3]

Definition of an embedding?

Hugging Face

An embedding is a numerical representation of a piece of information, for example, text, documents, images, audio, etc.

https://huggingface.co/blog/getting-started-with-embeddings

CLOUDFLARE

embeddings are *vectors* created by machine learning models for the purpose of capturing meaningful data about each object

https://www.cloudflare.com/learning/ai/what-are-embeddings/

Google

An **embedding** is a relatively low-dimensional space into which you can translate high-dimensional vectors. Embeddings make it easier to do machine learning on large inputs like sparse vectors representing words. Ideally, an embedding captures some of the semantics of the input by placing semantically similar inputs close together in the embedding space.

https://developers.google.com/machine-learning/crash-course/embeddings/video-lecture

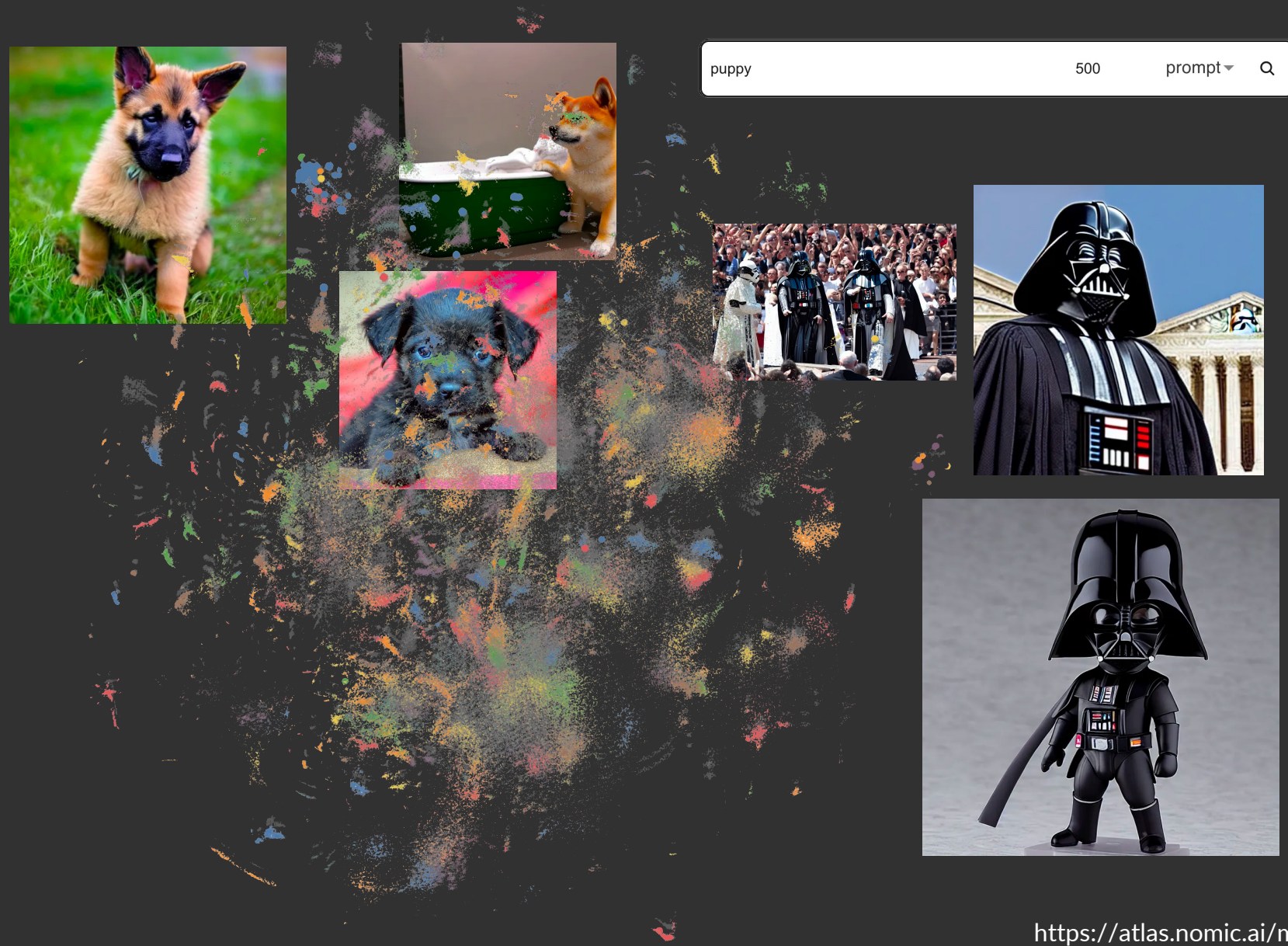
IBM

Embedding is a means of representing objects like text, images and audio as points in a continuous vector space where the locations of those points in space are semantically meaningful

https://developers.google.com/machine-learning/crash-course/embeddings/video-lecture

An **embedding** is a set of *coordinates in vector space* into which we map a concept.

Embedding concepts into a vector space

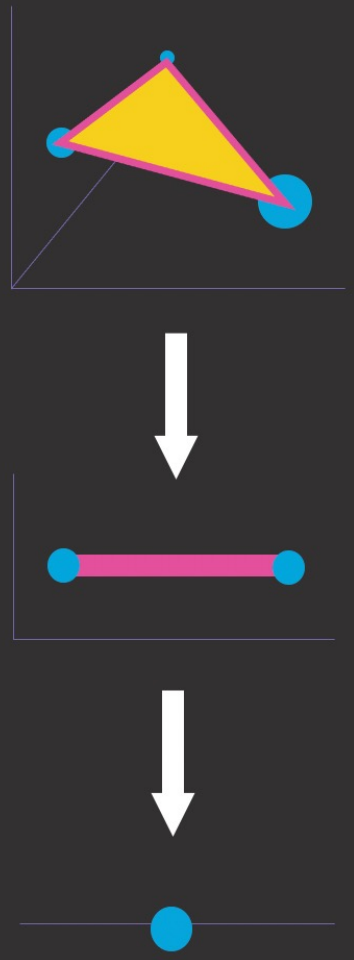


https://atlas.nomic.ai/map/stablediffusion

An inverted index creates embeddings, with one dimension per term

	apple	caffeine	cheese	coffee	drink	donut	food	juice	pizza	tea	water	… *term N*
latte	0	0	0	0	0	0	0	0	0	0	0	…
cappuccino	0	0	0	0	0	0	0	0	0	0	0	…
apple juice	1	0	0	0	0	0	0	1	0	0	0	…
cheese pizza	0	0	1	0	0	0	0	0	1	0	0	…
donut	0	0	0	0	0	1	0	0	0	0	0	…
soda	0	0	0	0	0	0	0	0	0	0	0	…
green tea	0	0	0	0	0	0	0	0	0	1	0	…
water	0	0	0	0	0	0	0	0	0	0	1	…
cheese bread sticks	0	0	1	0	0	0	0	0	0	0	0	…
cinnamon sticks	0	0	0	0	0	0	0	0	0	0	0	…

Embedding (verb) maps concepts into another vector space (usually a lower-dimensional space)



	food	drink	dairy	bread	caffeine	sweet	calories	healthy
apple juice	0	5	0	0	0	4	4	3
cappuccino	0	5	3	0	4	1	2	3
cheese bread sticks	5	0	4	5	0	1	4	2
cheese pizza	5	0	4	4	0	1	5	2
cinnamon bread sticks	5	0	1	5	0	3	4	2
donut	5	0	1	5	0	4	5	1
green tea	0	5	0	0	2	1	1	5
latte	0	5	4	0	4	1	3	3
soda	0	5	0	0	3	5	5	0
water	0	5	0	0	0	0	0	5

We then leverage the vector space to explore similarity

Phrase:	Vector:
apple juice:	[0, 5, 0, 0, 0, 4, 4, 3]
cappuccino:	[0, 5, 3, 0, 4, 1, 2, 3]
cheese bread sticks:	[5, 0, 4, 5, 0, 1, 4, 2]
cheese pizza:	[5, 0, 4, 4, 0, 1, 5, 2]
cinnamon bread sticks:	[5, 0, 4, 5, 0, 1, 4, 2]
donut:	[5, 0, 1, 5, 0, 4, 5, 1]
green tea:	[0, 5, 0, 0, 2, 1, 1, 5]
latte:	[0, 5, 4, 0, 4, 1, 3, 3]
soda:	[0, 5, 0, 0, 3, 5, 5, 0]
water:	[0, 5, 0, 0, 0, 0, 0, 5]

Vector Similarity (a, b):

$$\cos(\theta) = \frac{a \cdot b}{|a| \times |b|}$$

Vector Similarity Scores:

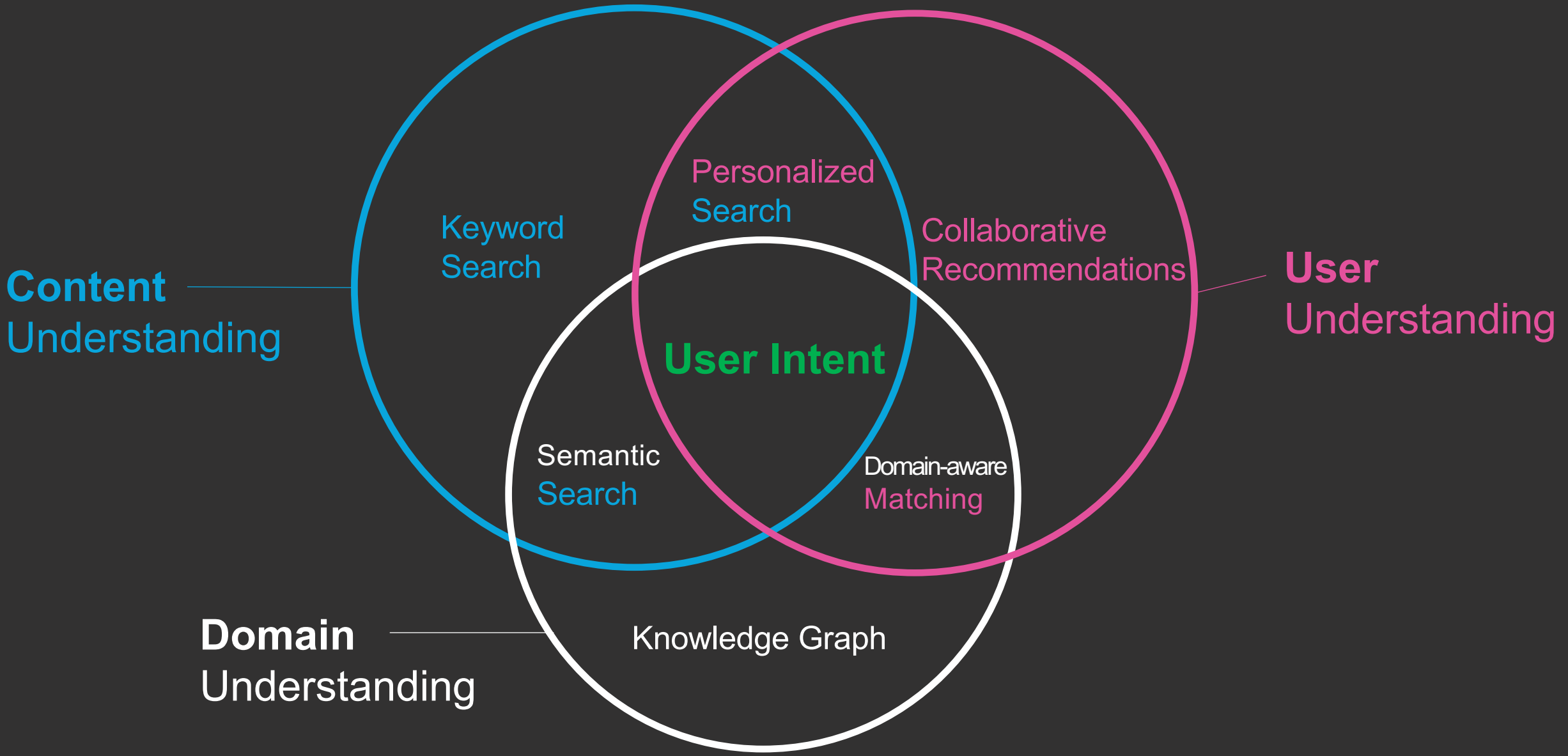
Ranked Results: Cheese Pizza	
0.99	cheese bread sticks
0.91	cinnamon bread sticks
0.89	donut
0.47	latte
0.46	apple juice
...	...
0.19	water

Ranked Results: Green Tea	
0.94	water
0.85	cappuccino
0.80	latte
0.78	apple juice
0.60	soda
...	...
0.19	donut

With LLMs and other Foundation Models, the dimensions learned are Latent Features*.

* We'll return to this later

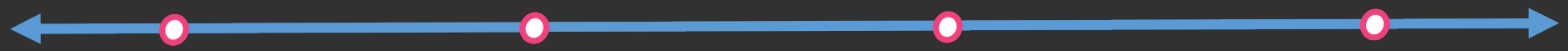
Dimensions of User Intent



Personalization Spectrum

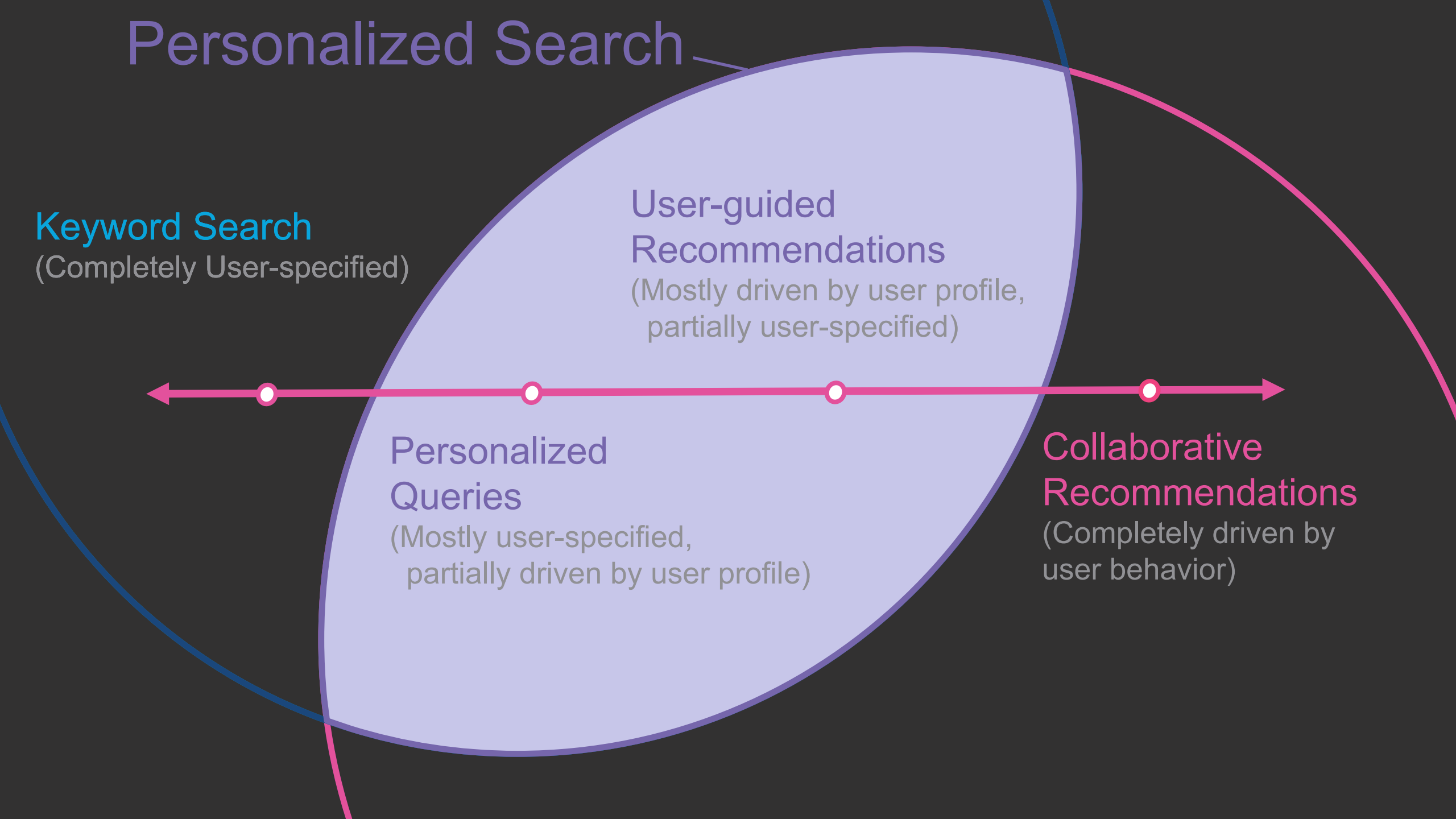
Traditional Keyword Search
(Completely User-specified)

User-guided Recommendations
(Mostly driven by user profile, partially user-specified)



Personalized Search
(Mostly user-specified, partially driven by user profile)

Traditional Recommendations
(Completely driven by user profile)


Personalized Search
Keyword Search
(Completely User-specified)
User-guided
Recommendations
(Mostly driven by user profile,
partially user-specified)
Personalized
Queries
(Mostly user-specified,
partially driven by user profile)
Collaborative
Recommendations
(Completely driven by
user behavior)

Recommendations Approaches

Content-based Matching (Content Filtering)

Recommendations:
-**fabric softener**
-**dryer sheets**

detergent

category: laundry
text: cleans clothes spotless and removes stains leaving a fresh citrus scent

fabric softener

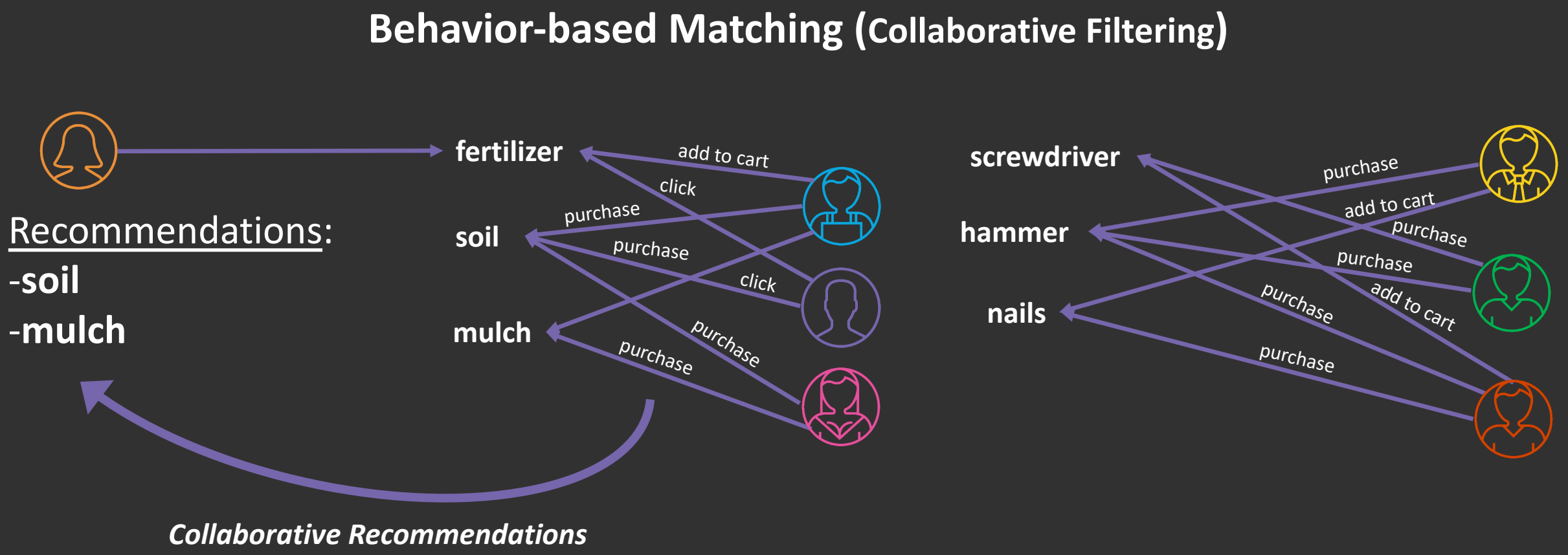
category: laundry
text: softens clothes and leaves a fresh citrus scent

dryer sheets

category: laundry
text: removes static electricity from clothes and leaves a fresh citrus scent

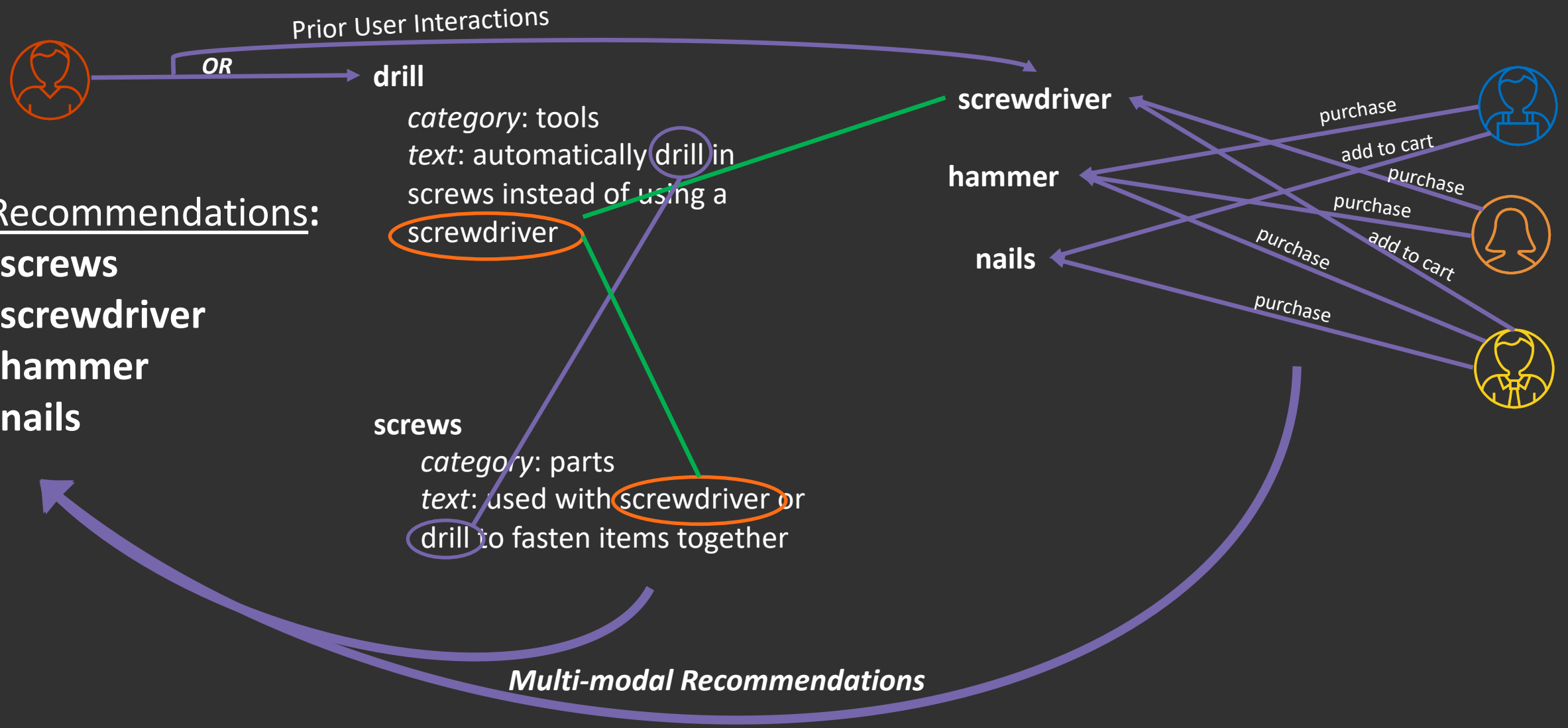
Content-based Recommendations

Recommendations Approaches



Recommendations Approaches

Content-based Matching (Content Filtering) + **Behavior-based Matching (Collaborative Filtering)**



Recommendations:

- **screws**
- **screwdriver**
- **hammer**
- **nails**

Collaborative Filtering

- User 1:
  - *Avengers: Endgame*
  - *Black Panther*
  - *Black Widow*
- User 2:
  - *Black Widow*
  - *Captain Marvel*
  - *Black Panther*
- User 3:
  - *Black Widow*
  - *The Dark Knight*
  - *The Batman*
- User 4:
  - *The Little Mermaid*
  - *The Lion King*
  - *Toy Story*
- User 5:
  - *Frozen*
  - *Toy Story*
  - *The Lion King*

Users 1-3:
- All of these are movies about superheroes
- Most of them were made by Marvel Studios, though some were made by Warner Brothers (DC Comics)
- They are all action movies
- They are not suitable for small children due to violence and/or language

Users 4-5:
- All of them are animated movies
- All of them are suitable for small children
- All of them are made by Disney/Pixar

Collaborative Filtering (Alternating Least Squares)

Alternating Least Squares (Matrix Factorization based Collaborative Filtering)

```python
from pyspark.ml.evaluation import RegressionEvaluator
from pyspark.ml.recommendation import ALS
from pyspark.sql import Row

als = ALS(maxIter=3, rank=10, regParam=0.15, implicitPrefs=True,
          userCol="userIndex", itemCol="productIndex", ratingCol="rating",
          coldStartStrategy="drop", seed=0)

(training, test) = indexed_prefs.randomSplit([0.8, 0.2], 0)

model = als.fit(indexed_prefs) (1)
predictions = model.transform(test) (1)
evaluator = RegressionEvaluator(metricName="rmse", labelCol="rating",
                                predictionCol="prediction")
rmse = evaluator.evaluate(predictions)
print(f"Root-mean-square error = {rmse}")

indexed_user_recs = model.recommendForAllUsers(10)
indexed_user_recs.show(5)
```

Results:

```
Root-mean-square error = 0.9589

+---------+--------------------+
|userIndex|     recommendations|
+---------+--------------------+
|        0|[{11, 0.014824464...|
|        1|[{5, 0.010805087}...|
|        2|[{7, 0.060263287}...|
|        3|[{1, 0.02967207},...|
|        4|[{14, 0.007906279...|
+---------+--------------------+
only showing top 5 rows
```

```
User: u478462

Previous Searches:
--apple
--macbook

Previous Product Interactions:
--type: click, name: Apple® - iPad® 2 with Wi-Fi - 16GB - Black
--type: add-to-cart, name: Apple® - iPad® 2 with Wi-Fi - 16GB - Black
--type: purchase, name: Apple® - iPad® 2 with Wi-Fi - 16GB - Black
--type: click, name: Apple® - MacBook® Air - Intel® Core™ i5 Processor ...
```

Alternating Least Squares (Matrix Factorization based Collaborative Filtering)

```python
def get_query_time_boosts(user, boosts_collection):
  request = {"query": "",
             "return_fields": ["product", "boost"],
             "filters": [("user", user)] if user else [],
             "limit": 10,
             "order_by": [("boost", "desc")]}

  response = boosts_collection.search(request)
  signals_boosts = response["docs"]
  return " ".join(f'"{b["product"]}"^{b["boost"] * 100}' for b in signals_boosts)

def run_main_query(query, signals_boosts):
  request = product_search_request(query if query else "")
  request["query_boosts"] = signals_boosts if signals_boosts else "*"
  return products_collection.search(request)

recs_collection = engine.get_collection("user_item_recommendations")
user = "u478462"
boosts = get_query_time_boosts(user, recs_collection)

response = run_main_query(None, boosts)

print(f"Boost Query:\n{boosts}")
display_product_search("", response["docs"])
```

```
Boost Query:
"885909457588"^75.393623 "097360810042"^18.904798 "821793013776"^15.852094 "610839379408"^10.217768000000001 "635753493559"^9.087185 "885909395095"^8.304988 "885909457595"^7.9175640000000005 "885909431618"^7.375394 "885909459858"^6.592548 "885909436002"^6.1031554

Recommendations:
```

Search

Name: Apple® - iPad® 2 with Wi-Fi - 16GB - Black | **Manufacturer:** Apple®

9.7" widescreen display; 802.11a/b/g/n Wi-Fi; Bluetooth; iBooks support; measures just 0.34" thin and weighs only 1.35 lbs.

Name: HTC - Flyer Tablet with 16GB Internal Memory - White | **Manufacturer:** HTC

Android 2.3 Gingerbread operating system7" color touch screenWi-Fi16GB memoryHTC notes, Watch and Listen apps

Name: Asus - Eee Pad Transformer Tablet with 16GB Storage Memory - Brown/Black | **Manufacturer:** Asus

Android 3.0 Honeycomb10.1" WXGA IPS touch screen Wi-Fi16GB hard drive

Name: Samsung - Galaxy Tab 10.1 - 16GB - Metallic Gray | **Manufacturer:** Samsung

Android 3.1 (Honeycomb) operating system10.1" WXGA touch screenWi-Fi

Name: Apple® - iPod touch® 32GB* MP3 Player (4th Generation - Latest Model) - Black | **Manufacturer:** Apple®

FaceTime camera, HD video recording, Retina display, Multi-Touch interface; gorgeous 3.5" widescreen display; Wi-Fi Web browsing

Name: Apple® - iPad® 2 with Wi-Fi - 32GB - Black | **Manufacturer:** Apple®

9.7" widescreen display; 802.11a/b/g/n Wi-Fi; Bluetooth; iBooks support

Non-personalized Search Results

```python
query = "tablet"

response = run_main_query(
  query, None, 7
)
print(f"Non-personalized Query")
display_product_search(
  query, response["docs"]
)
```

Non-personalized Query

tablet Search

Name: Init™ - Tablet Sleeve - Olive | **Manufacturer:** Init™

Fits most tablets with up to a 10" display; heavy-duty neoprene material

---

Name: Memorial Tablet - CD | **Manufacturer:** Ltm/cd41

Name: Stone Tablet - CD | **Manufacturer:** Important Records

---

Name: Sony - AC Power Adapter for Sony Tablet S | **Manufacturer:** Sony

Compatible with Sony Tablet S; charges your tablet

Personalized Search Results

```
query = "tablet"

recs_collection = engine.get_collection(
  "user_item_recommendations"
)
user = "u478462"
boosts = get_query_time_boosts(
  user, recs_collection
)

response = run_main_query(query, boosts, 7)
print(f"Personalized Query")
display_product_search(query, response["docs"])
```

Personalized Query

tablet Search

Name: Apple® - iPad® 2 with Wi-Fi - 16GB - Black | **Manufacturer:** Apple®

9.7" widescreen display; 802.11a/b/g/n Wi-Fi; Bluetooth; iBooks support; measures just 0.34" thin and weighs only 1.35 lbs.

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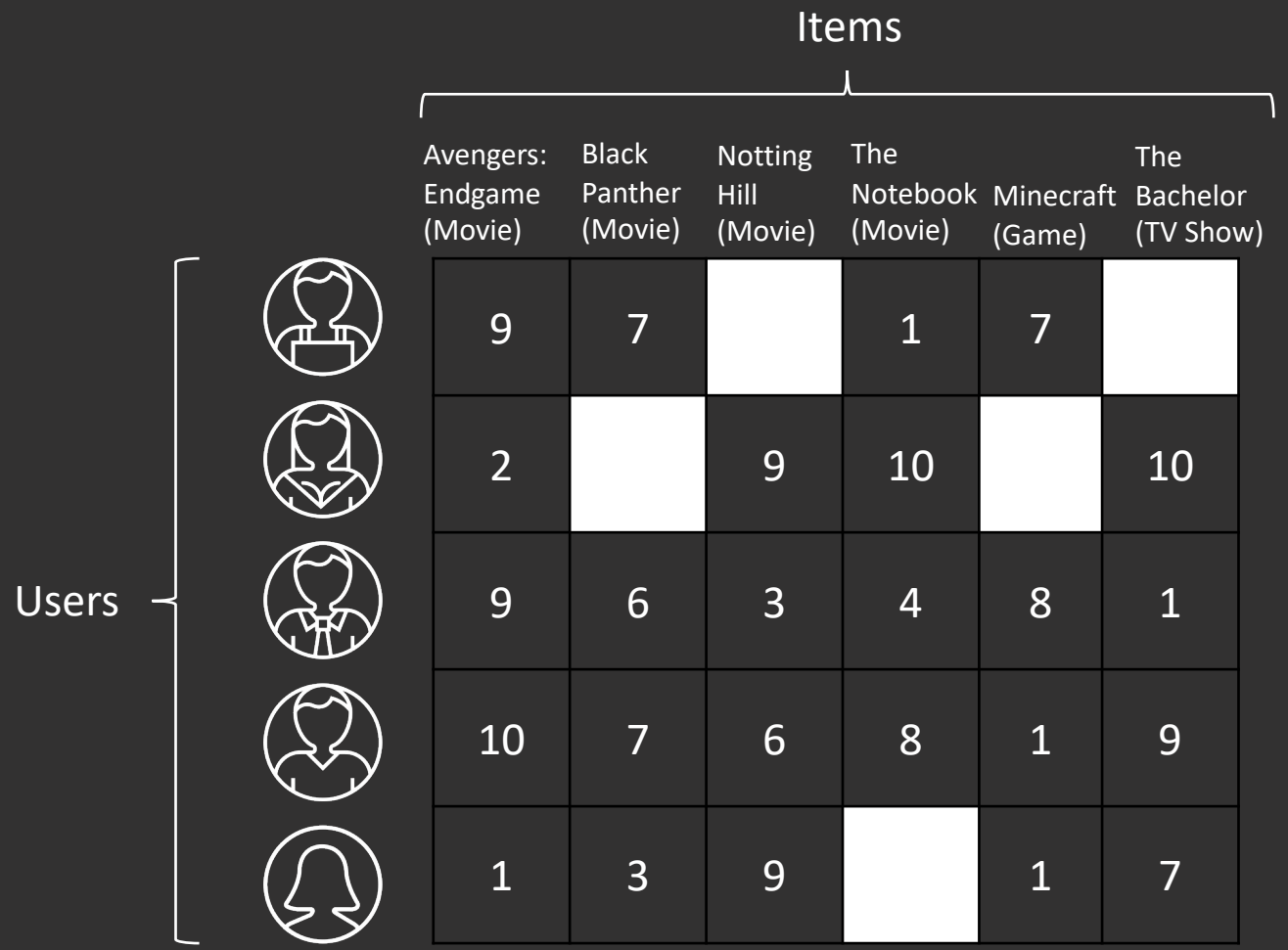
Personalizing search using embeddings

Learned embeddings are latent features

Items

Latent Features (Content-based)								
	1	4.1	4.1	8.2	7.7	1.9	4.0	≈ size?
	2	9.8	1.2	2.2	0.8	1.2	0.3	≈ color?
	3	9.9	9.9	3.2	1.7	9.2	0.2	≈ computer-like?
	...	...	...	...	...	...	...	
	768	3.0	3.0	7.3	5.9	4.3	0.3	≈ price?

User-Item Interaction Matrix



Matrix Factorization… learning latent features from user signals

User-Item Rankings (R)

User Feature Matrix (U)

Item Feature Matrix (I)

Learning embeddings of USERS allows us to personalize search results

Current search: microwave

Previous Interactions:

Hello Kitty Plush Toy	**GE** Electric Razor (**Black**)
GE Bright **White** Light Bulbs	**Samsung Stainless-steel** Refrigerator

No personalization guardrails:

GE - 0.7 Cu. Ft. Compact Microwave - Black

Cook or reheat your meals in minutes with this compact 700-watt microwave oven that features instant-on LED controls which heat food with the simple touch of a button. It also provides peace of mind with a control lockout feature that locks the microwave when it's not in use.

Dept Appliance Brand GE Color Black

Hello Kitty - 0.7 Cu. Ft. Compact Microwave

Cook your favorite treats in this microwave that features 6 preprogrammable recipes for customized use and a compact design for optimal placement.

Dept Photo/Commodities Brand Hello Kitty

GE - 1.1 Cu. Ft. Mid-Size Microwave - White

Prepare hassle-free meals and snacks with this

vs.

With categorical personalization guardrails:

Samsung - Mid-Size Microwave - Stainless-steel

This mid-size microwave is large enough for almost any meal, but compact enough to fit into almost any space. Take an interactive product tour of this Samsung Microwave! (479KB Flash demo)

Dept Appliance Brand Samsung Color Stainless-Steel

Samsung - 1.7 Cu. Ft. Over-the-Range Microwave - Stainless-Steel

The capabilities of a toaster oven, convection oven, range hood and microwave combine in this microwave that features a 1.7 cu. ft. capacity for simultaneously cooking multiple dishes and sensor cook options to take the guesswork out of quick meal prep.

Dept Appliance Brand Samsung Color Stainless-

Clustering products by embedding to generate dynamic categories

Clustering products to generate dynamic category contexts

```
def get_clusters(data, algorithm, args, kwds):
  return algorithm(*args, **kwds).fit(data)

def assign_clusters(labels, product_names):
  clusters = defaultdict(lambda:[], {})
  for i in range(0, len(labels)):
    clusters[labels[i]].append(product_names[i])
  return clusters

algo = get_clusters(product_embeddings, cluster.KMeans, (),
                    {"n_clusters":100, "n_init":10, "random_state":0}) #<1>
labels = algo.predict(product_embeddings)
clusters = assign_clusters(labels, product_names) #<2>

#<1> Generate 100 clusters using a KMeans clustering algorithms
#<2> Assign each product name to its corresponding cluster label
```

Visualizing the clusters

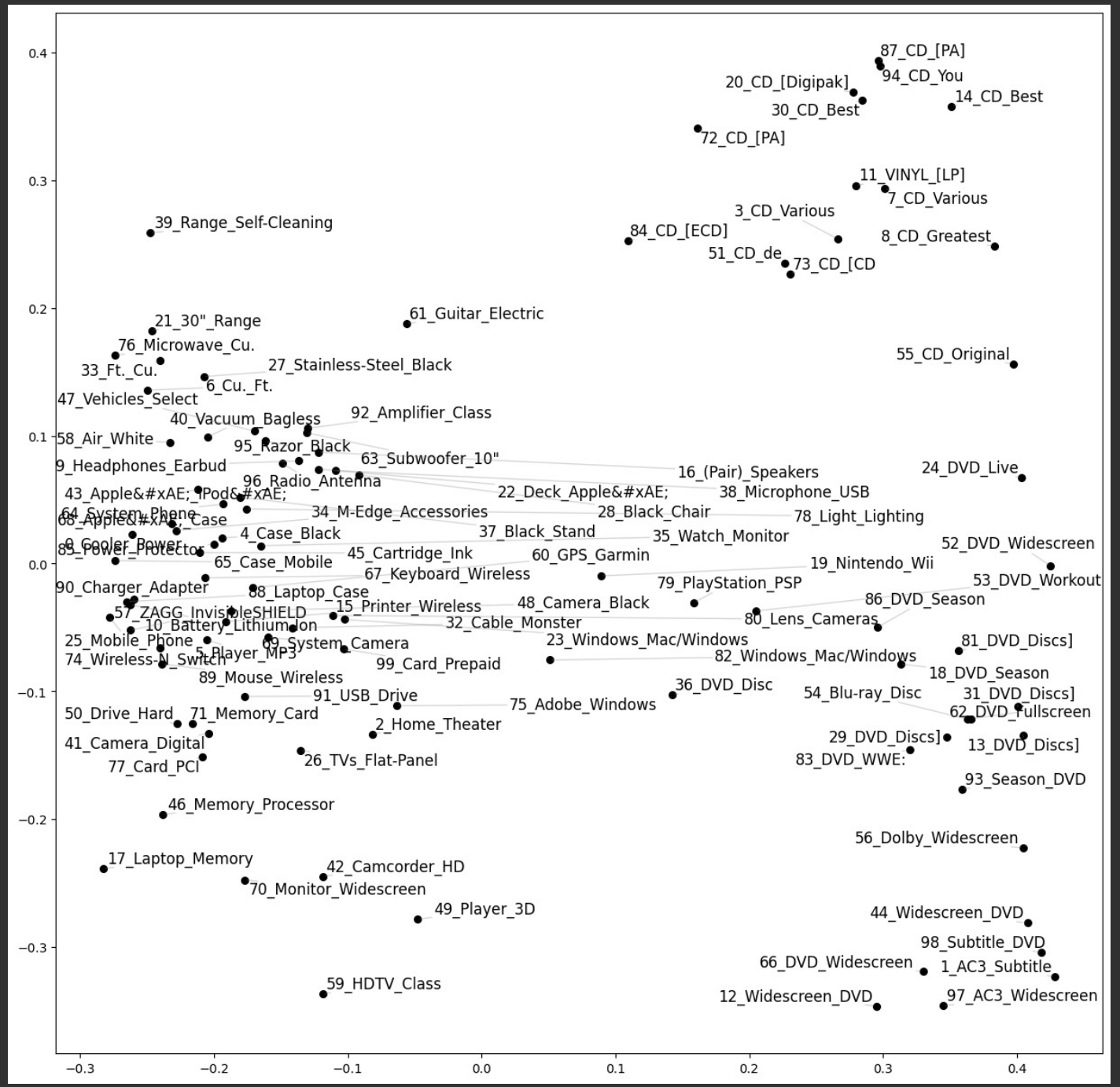
Visualize the category contexts

```
import collections, numpy as np, matplotlib.pyplot as plt
from adjustText import adjust_text
from sklearn.decomposition import PCA

plt.figure(figsize=(15, 15))
pca = PCA(100, svd_solver="full")
centers = algo.cluster_centers_
plot_data = pca.fit_transform(centers) #<1>

points = []
for i, cluster_name in enumerate(plot_data): #<2>
  plt.scatter(plot_data[i,0], plot_data[i,1], #<3>
              s=30, color="k")  (2)
  label = f"{i}_{"_".join(top_words(clusters[i], 2))}"
  points.append(plt.text(plot_data[i,0], #<3>
                         plot_data[i,1], #<3>
                         label, size=12)) #<3>
adjust_text(points, arrowprops=dict(arrowstyle="-", #<4>
                          color="gray", alpha=.3)) #<4>
plt.show()

#<1> Perform PCA to reduce to 2 dimensions for visualization
#<2> Loop through each cluster and plot it on the graph
#<3> Add a text label for each cluster with the cluster ID
#    and top-N words in each cluster
#<4> Display improvement: adjust the text labels to
#    minimize overlap
```



Mapping queries into clusters (multiple approaches)

Different approaches for mapping queries into clusters

```python
import sentence_transformer, heapq

def get_top_labels_centers(query, centers, n=2): #<4>
  q_emb = transformer.encode([query], convert_to_tensor=False)
  similarities = sentence_transformers.util.cos_sim(q_emb, centers)
  sim = similarities.tolist()[0]
  return [sim.index(i) for i in heapq.nlargest(n, sim)]

def get_query_cluster(query): #<5>
  q_emb = transformer.encode([query], convert_to_tensor=False)
  return algo.predict(q_emb)

def get_cluster_description(cluser_num):
  return "_".join(top_words(clusters[cluser_num], 5))

query = "microwave"
kmeans_predict = get_query_cluster(query)[0] #<1>
print("KMeans Predicted Cluster:")
print(f"    {kmeans_predict} ({get_cluster_description(kmeans_predict)})")

closest_sim = get_top_labels_centers(query, centers, 1)[0] #<2>
print(f"\nCosine Predicted Cluster:")
print(f"    {closest_sim} ({get_cluster_description(closest_sim)})")

knn_cosine_similarity = get_top_labels_centers(query, centers, 5) #<3>
print(f"\nKNN Cosine Predicted Clusters: {knn_cosine_similarity}")
for n in knn_cosine_similarity:
      print(f"    {n} ({get_cluster_description(n)})")

#<1> Option 1: Predict nearest cluster (KMeans)
#<2> Option 2: Find most-similar cluster (Cosine similarity)
#<3> Option 3 (recommended): Find N-most-similar clusters (Cosine similarity)
#<4> Get the top N clusters based on cosine similarity with the cluster centroids
#<5> Get the cluster based on the KMeans model's prediction
```

Results:

```
KMeans Predicted Cluster:
  76 (Microwave_Cu._Ft._Stainless-Steel_Oven)

Cosine Predicted Cluster:
  76 Microwave_Cu._Ft._Stainless-Steel_Oven)

KNN Cosine Predicted Clusters: [76, 27, 21, 39, 33]
  76 (Microwave_Cu._Ft._Stainless-Steel_Oven)
  27 (Stainless-Steel_Black_KitchenAid_Cuisinart_Maker)
  21 (30"_Range_Stainless-Steel_Gas_Cooktop)
  39 (Range_Self-Cleaning_30"_Freestanding_Stainless-Steel)
  33 (Ft._Cu._Refrigerator_Water_Thru-the-Door)
```

Approaches for integrating embedding-based personalization into search results

- Perform a weighted average between the query vector (embedding for microwave) and the vectors for the user's previous interactions within the predicted clusters. This would generate a single vector representing a personalized version of the user's query, so all results would be personalized.

- Perform a standard search, but then boost the results based on the average of the embeddings from a user's previous interactions within the predicted clusters. This would be a hybrid keyword and vector-based ranking function, where the keyword search would be the primary driver of the results, but the user's previous interactions would be used to boost related results higher.

- Do one of the above, but then only personalize a few items in the search results instead of all the results. This follows a light-touch mentality so as not to disturb all of the user's search results, while still injecting novelty to enable the user to discover personalized items they may not have otherwise found.

- Perform a standard search (keyword or vector), but then re-rank the results based on the weighted average between the query vector and the vectors for the user's previous interactions within the predicted clusters. This uses the original search to find the candidate results using the default relevance algorithm, but then those results are re-ranked to boost personalized preferences higher.

Generating personalization vectors for a user's query

Generating a personalization vector for the user's query

```python
import pandas, numpy

def get_user_embeddings(products=[]): #<1>
  values = []
  for p in products:
    values.append([product_ids_emb[p],
                   top_clusters_for_embedding(product_ids_emb[p], 1)[0]])
  column_names = ["embedding", "cluster"]
  return pandas.DataFrame(data=numpy.array(values), index=products,
                          columns=column_names)

def get_personalization_vector(query=None, #<2>
                               user_items=[],
                              query_weight=1, #<3>
                     user_items_weights=[]): #<4>
  query_embedding = transformer.encode(query) if query else None

  if len(user_items) > 0 and len(user_items_weights) == 0: #<3>
    user_items_weights = numpy.full(shape=len(user_items),
                                    fill_value=1 / len(user_items))

  embeddings = []
  embedding_weights = []
  for weight in user_items_weights: #<4>
    embedding_weights.append(weight) #<4>
  for embedding in user_items:
    embeddings.append(embedding)
  if query_embedding.any():
    embedding_weights.append(query_weight) #<4>
    embeddings.append(query_embedding)

  return numpy.average(embeddings, weights=numpy.array(embedding_weights),
                       axis=0).astype("double") if len(embeddings) else None

#<1> Returns a dataframe with the embedding and guardrail cluster for each product
#<2> Returns a vector that combines (weighted average) an embedding for the query
#    with the embeddings for the passed-in user_items
#<3> By default, the weight is split 1:1 (50% each) between the query embedding
#    and the user_items_weight
#<4> You can optionally specify a query_weight and user_item_weights to influence
#    how much each embedding influences the personalization vector
```

Generating contextual user personalization vectors

Contextual (filtered) vs. Non-contextual (unfiltered) personalization vectors

```python
product_interests = ["7610465823828", #hello kitty water bottle
                     "36725569478"] #stainless steel electric range

user_embeddings = get_user_embeddings(product_interests)
query = "microwave"

unfiltered_personalization_vector = get_personalization_vector(query=query,
  user_items=user_embeddings['embedding'].to_numpy()) #<1>
print("\nPersonalization Vector (No Cluster Guardrails):")
print(format_vector(unfiltered_personalization_vector))

query_clusters = get_top_labels_centers(query,
                                centers, n=5) #<2>
print("\nQuery Clusters ('microwave'):\n" + str(query_clusters))

clustered = user_embeddings.cluster.isin(query_clusters) #<3>
products_in_cluster = user_embeddings[clustered] #<3>
print("\nProducts Filtered to Query Clusters:\n" + str(products_in_cluster))

filtered_personalization_vector = get_personalization_vector(query=query,
  user_items=filtered['embedding'].to_numpy()) #<4>
print("\nFiltered Personalization Vector (With Cluster Guardrails):")
print(format_vector(filtered_personalization_vector))

#<1> Personalization vector with no guardrails
#    (uses query and all past item interactions)
#<2> Get the top 5 clusters for the query to use as guardrails
#<3> Filter down to only items in the guardrail query clusters
#<4> Generate a personalization vector with guardrails
#    (uses query and only items related to the query)
```

Results:

```
Products Interactions for Personalization:
product        embedding                                              cluster
7610465823828  [0.06417941, 0.04178553, -0.0017139615, -0.020...]  28
36725569478    [0.0055417763, -0.024302201, -0.024139373, -0....]  39

Personalization Vector (No Cluster Guardrails):
[0.016, -0.006, -0.02, -0.032, -0.016, 0.008, -0.0, 0.017, 0.011, 0.007,...]

Query Clusters ('microwave'):
[76, 27, 21, 39, 33]

Products Filtered to Query Clusters:
product      embedding                                                cluster
36725569478  [0.0055417763, -0.024302201, -0.024139373, -0....]  39

Filtered Personalization Vector (With Cluster Guardrails):
[0.002, -0.023, -0.026, -0.037, -0.025, 0.002, -0.009, 0.007, 0.033, -0....]
```

Run different personalization scenarios

Run Different Personalization Scenarios

```
def rerank_with_personalization(docs, personalization_vector):
  result_embeddings = numpy.array([product_ids_emb[docs[x]["upc"]]
                                   for x in range(len(docs))]).astype(float)
  similarities = sentence_transformers.util.cos_sim(
      personalization_vector, result_embeddings).tolist()[0]
  reranked = [similarities.index(i)
              for i in heapq.nlargest(len(similarities), similarities)]
  reranked, v = zip(sorted(enumerate(similarities),
                           key=itemgetter(1), reverse=True))
  return [docs[i] for i in reranked]

query = "microwave"
request = {"query": query,
           "query_fields": ["name", "manufacturer"],
           "return_fields": ["upc", "name", "manufacturer", "score"],
           "limit": 100,
           "order_by": [("score", "desc"), ("upc", "asc")]}

response = products_collection.search(*request)
docs = response["docs"]
print("No Personalization:")
display_product_search(query, docs[0:4])

print("Global Personalization (no category guardrails):")
reranked_seach_results_no_guardrails = \
  rerank_with_personalization(docs,
    unfiltered_personalization_vector)
display_product_search(query, reranked_seach_results_no_guardrails[0:4])

print("Contextual Personalization (with category guardrails):")
reranked_seach_results_with_guardrails = \
  rerank_with_personalization(docs,
    filtered_personalization_vector)
display_product_search(query, reranked_seach_results_with_guardrails[0:4])
```

No Personalization

microwave Search

Name: LG - LMHM2017SW Microwave Oven - White |
Manufacturer: LG

Name: Panasonic - NNCD989S Microwave Oven - Stainless-Steel |
Manufacturer: Panasonic

Name: West Bend - Microwave Popcorn Popper - Red |
Manufacturer: West Bend

Name: Hello Kitty - 0.7 Cu. Ft. Compact Microwave |
Manufacturer: Hello Kitty

Global Personalization (No Category Guardrails)

microwave Search

Name: Hello Kitty - 0.7 Cu. Ft. Compact Microwave |
Manufacturer: Hello Kitty

Name: Electrolux - 1.5 Cu. Ft. Built-In Microwave - Stainless-Steel |
Manufacturer: Electrolux

Name: Panasonic - 1.2 Cu. Ft. Mid-Size Microwave - Stainless-Steel | **Manufacturer:** Panasonic

Name: Panasonic - 1.2 Cu. Ft. Mid-Size Microwave - White |
Manufacturer: Panasonic

Contextual Personalization (with Category Guardrails)

microwave Search

Name: Electrolux - 1.5 Cu. Ft. Built-In Microwave - Stainless-Steel |
Manufacturer: Electrolux

Name: Panasonic - 1.2 Cu. Ft. Mid-Size Microwave - Stainless-Steel | **Manufacturer:** Panasonic

Name: Panasonic - 2.2 Cu. Ft. Full-Size Microwave - Stainless-Steel | **Manufacturer:** Panasonic

Name: Panasonic - 2.2 Cu. Ft. Full-Size Microwave - Stainless-Steel | **Manufacturer:** Panasonic

Multimodal models (language + behavior) can integrate these latent features to discover new insights and enhance relevance

0.67	-0.51	2.81
1.13	3.18	-0.13
1.66	-0.08	2.50
-0.05	2.76	2.29
2.20	2.16	-0.20

×

Avengers: Endgame (Movie)	Black Panther (Movie)	Notting Hill (Movie)	The Notebook (Movie)	Minecraft (Game)	The Bachelor (TV Show)
0.09	0.71	1.91	1.74	1.80	0.28
0.75	0.75	2.17	2.54	-1.17	3.02
3.43	2.21	0.01	0.46	1.89	0.30

=

Avengers: Endgame (Movie)	Black Panther (Movie)	Notting Hill (Movie)	The Notebook (Movie)	Minecraft (Game)	The Bachelor (TV Show)
9.32	6.30	**0.20**	1.16	7.11	**-0.51**
2.04	**2.90**	9.06	9.98	**-1.93**	9.88
8.66	6.64	3.02	3.84	7.81	0.97
9.92	7.10	5.92	7.98	1.01	9.01
1.13	2.74	8.89	**9.22**	1.05	7.08

Calculating Preferences from Latent Factors:

Avengers: Endgame (Movie)

(0.67 * 0.09) + (-0.51 * 0.75) + (2.81 * 3.43) =

9.32

The Notebook (Movie)

(1.13 * 1.74) + (3.18 * 2.54) + (-0.13 * 0.46) =

9.98

Multimodal Vector Search

Image Encoder Layer

Text Encoder Layer

... "but I like to be here. Oh, I like it a lot!" said the Cat in the Hat to the fish in the pot...

[[0.00, 1.3, 26.9, 0.23, 0.0, 1.3, ...],

[0.19, 82.3, 0.02, 0.0, 0.0, 99.1, ...],

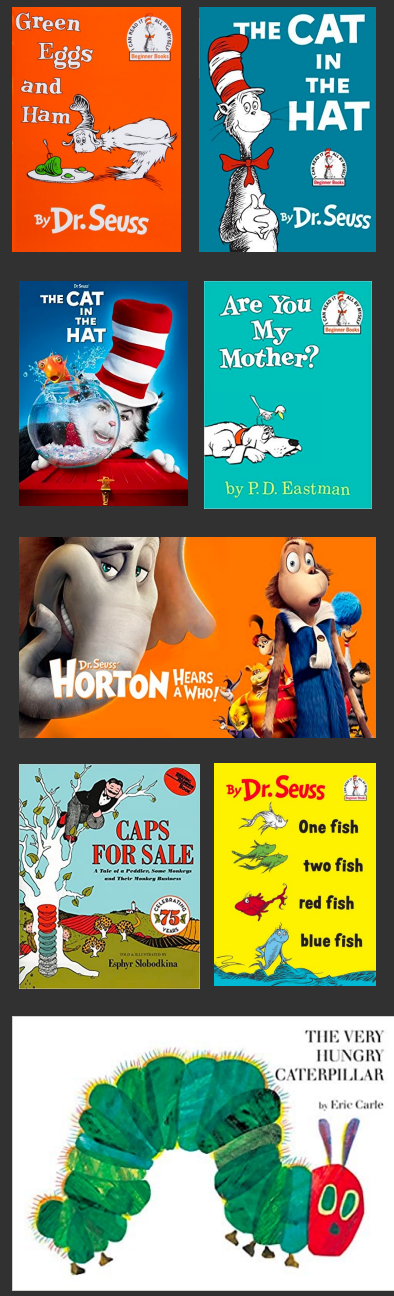
[0.00, 1.3, 26.9, 0.23, 0.0, 1.3, ...]]

Concatenate

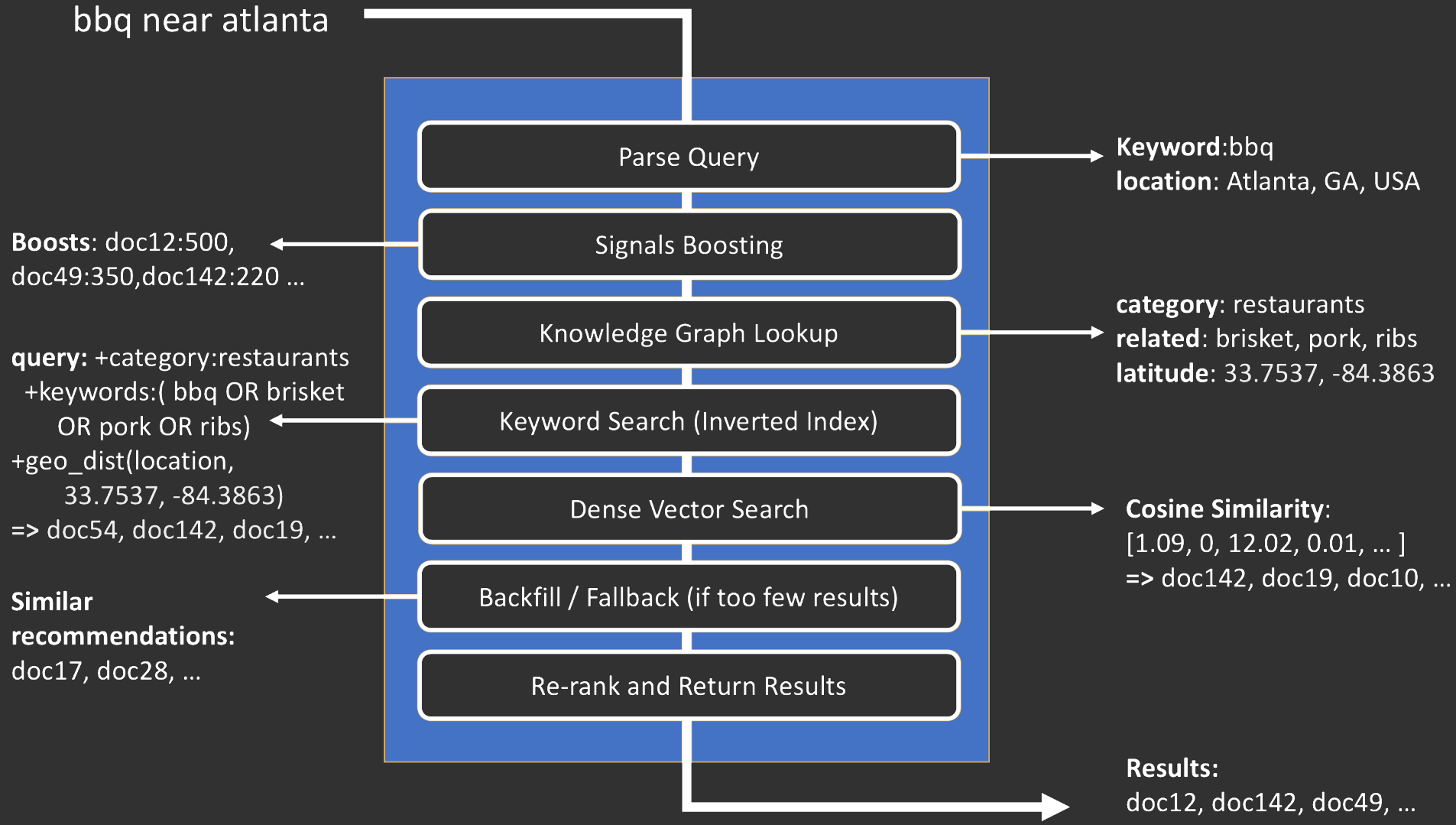
[0.00, 1.3, 26.9, 0.23, 0.0, 1.3, ..., 82.3, 0.02, 0.0, 0.0, 99.1, ..., 0.00, 1.3, 26.9, 0.23, 0.0, 1.3, ...]

Multimodal Encoder / Dimensionality Reduction

Collaborative User Signals Encoder Layer



It's also powerful to use many *query modalities* to optimize search quality



Reflected Intelligence: So many ways to integrate user signals…

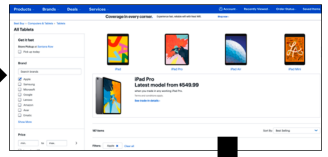
Signals Boosting Feedback Loop

1. User searches for "ipad"

2. Search logged and current model applied

User	Query
Alonzo	ipad
Elena	printer
Ming	tablet

3. Search returns boosted results



4. User takes action

User	Action	Document
Alonzo	click	doc22
Elena	click	doc17
Ming	click	doc12
Alonzo	purchase	doc22
Ming	click	doc22
Ming	purchase	doc22

5. Doc Interactions Aggregated Per Query

Query	Document	Signal Boost
ipad	doc22	54,321
ipad	doc12	987
printer	doc17	1,234
printer	purchase	2,345

6. Model improved for future searches

query: ipad
boost: doc22^54321
boost: doc12^987

Collaborative Filtering (Recommendations)

Recommendations for Alonzo:
- **doc22**: "iPad Pro"
- **doc12**: "Kindle Fire"
- …

ipad

User	Query
Alonzo	ipad
Elena	printer
Ming	ipad
…	…

User Searches

Users' actions inform system improvements

User Sees Results

User takes an action

User	Action	Document
Alonzo	click	doc22
Elena	click	doc17
Ming	click	doc12
Alonzo	purchase	doc22
Ming	click	doc22
Ming	purchase	doc22
Elena	click	doc2
…	…	…

Matrix Factorization

User	Item	Weight
Alonzo	doc22	1.0
Alonzo	doc12	0.4
…	…	…
Ming	doc12	0.9
Ming	doc22	0.6
…	…	…

Learning to Rank

ipad

Initial Results:
1) doc1
2) doc2
3) doc3

Final Results:
1) doc3
2) doc1
3) doc2

User	Query
Alonzo	ipad
Elena	printer
Ming	ipad
…	…

User Searches

Users' actions inform system improvements

User Sees Results

User takes an action

User	Action	Document
Alonzo	click	doc22
Elena	click	doc17
Ming	click	doc12
Alonzo	purchase	doc22
Ming	click	doc22
Ming	purchase	doc22
Elena	click	doc2
…	…	…

Feature	Weight
title_match_any_terms	15.25
is_known_category	10
popularity	9.5
content_age	9.2
…	…

Build Ranking Classifier
(from Implicit Relevance Judgements)

Related docs for Alonzo:
- **doc22**: "iPad Pro"
- **doc12**: "Kindle Fire"
- …

User	Document	Weight
Alonzo	doc22	1.0
Alonzo	doc12	0.4
…	…	…
Ming	doc12	0.9
Ming	doc22	0.6
…	…	…

Personal Preferences for Alonzo:
- **category**: "tablets"
  - **brand**: "Apple"
  - **color**: "black"
  - **storage**: "32GB"
- …

User	Preferences	Weight
Alonzo	[tablets] Brand: Apple color: black storage: 32GB	1.0
Trey	[appliances] Brand: Samsung color: stainless steel	0.4
…	…	…

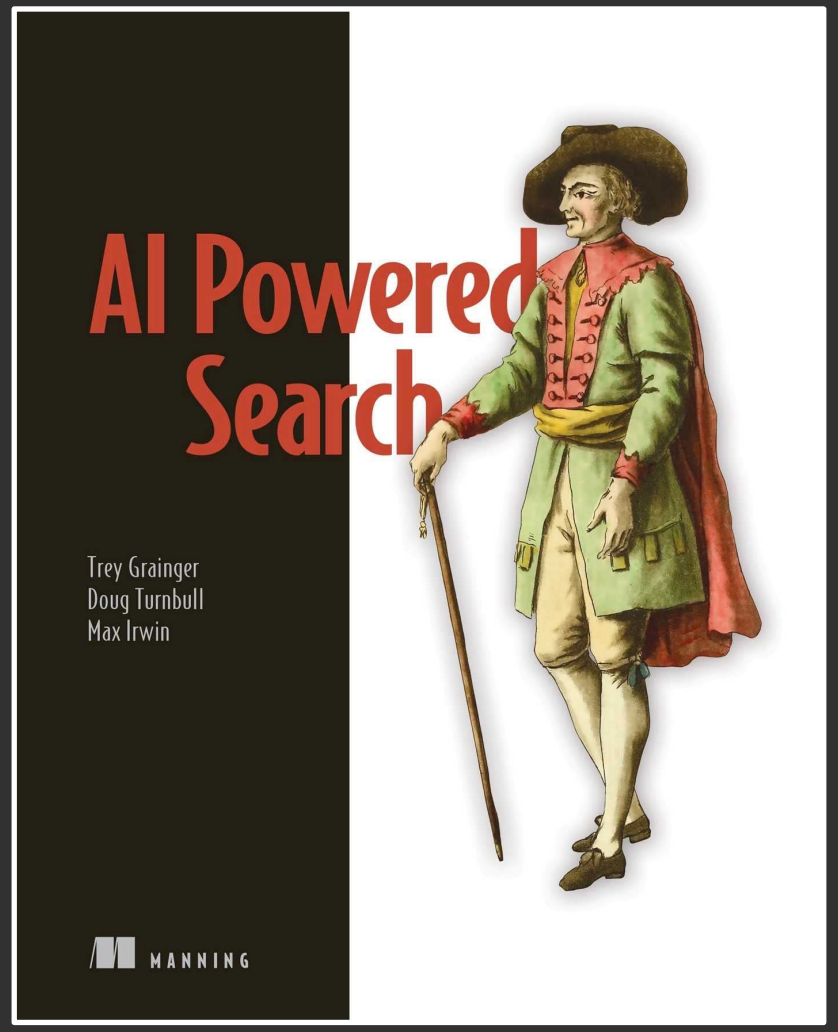
Related docs for doc22:
- **doc22**: "iPad Pro"
- **doc12**: "Kindle Fire"
- …

Item	Document	Weight
doc22	doc22	1.0
doc22	doc12	0.85
…	…	…
doc12	doc12	1.0
doc12	doc22	0.83
…	…	…

Related docs for query "ipad":
- **doc22**: "iPad Pro"
- **doc12**: "Kindle Fire"
- …

Query	Document	Weight
ipad	doc22	0.98
ipad	doc12	0.6
…	…	…
kindle	doc12	0.96
apple	doc22	0.90
…	…	…

Signal Processing & Machine Learning



AI-Powered Search

- RAG (Retrieval Augmented Generation)
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- Learning to Rank
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- Dense Vector Search
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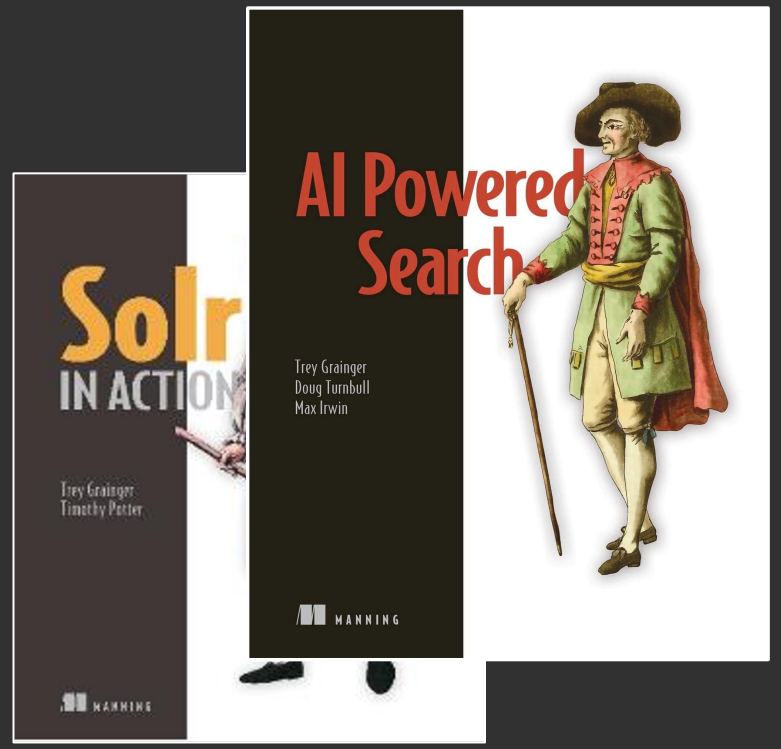

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