Deep Learning for Search and Recommender Systems in Practice

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LinkedIn
KDD 2020

Agenda

- Introduction
- Query&User Understanding
- Candidate Retrieval
- Learning to Rank

LinkedIn

Deep Learning for Search and Recommender Systems in Practice

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Introduction

Bo Long

Jun Jia

Introduction

1 **Search and Recommender Systems**

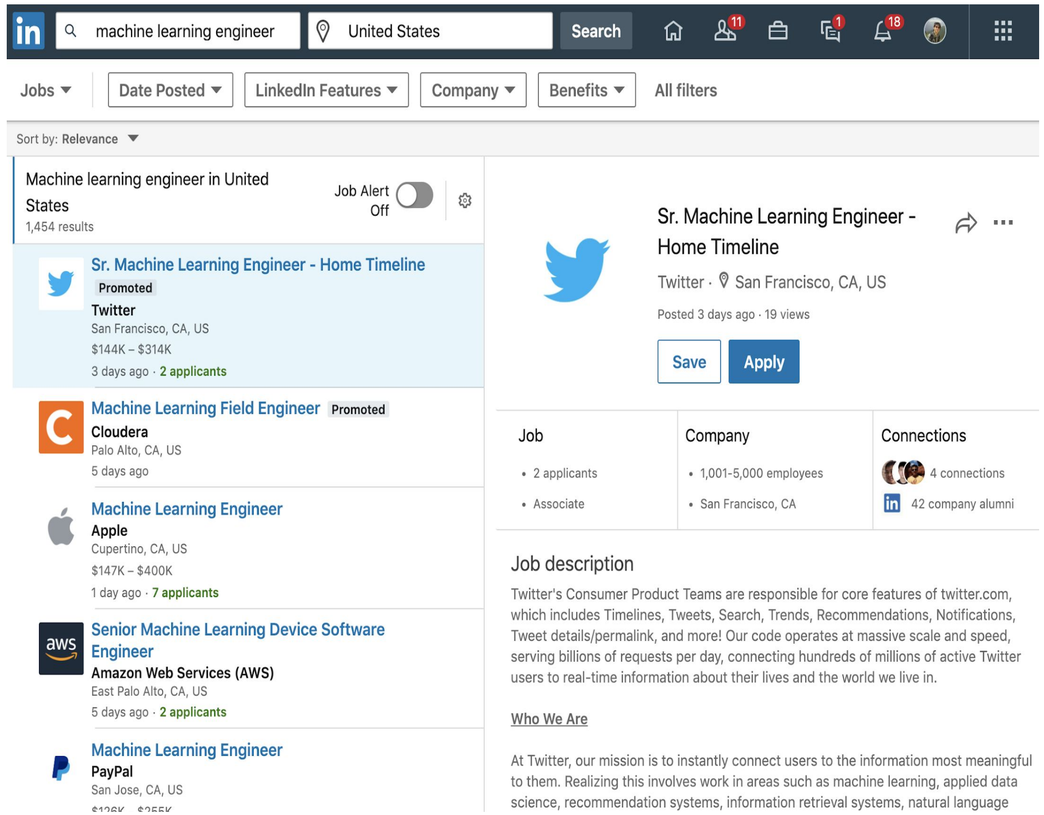
2 Applications at LinkedIn

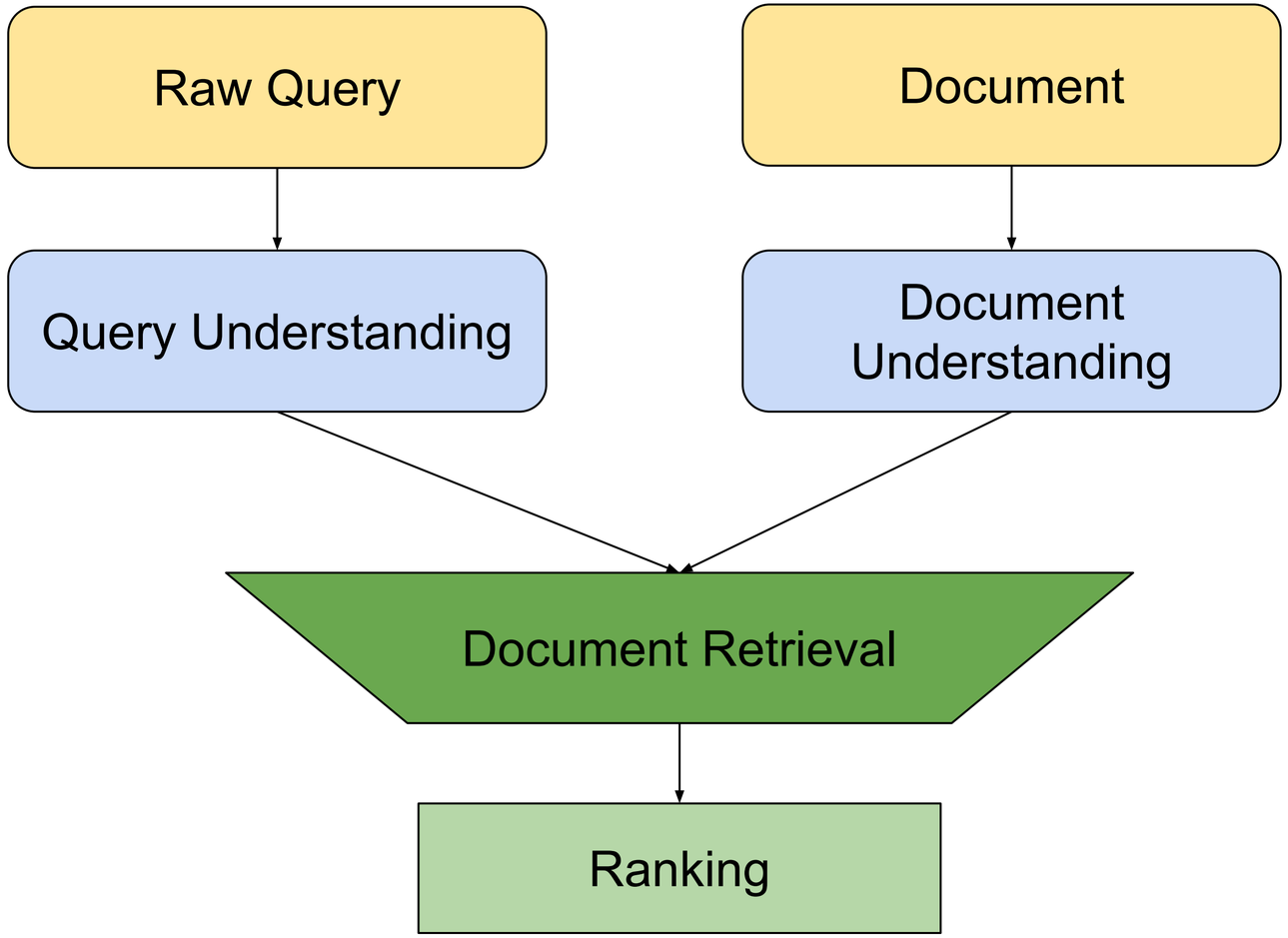
3 Tutorial Overview

Introduction - Search and Recommender Systems

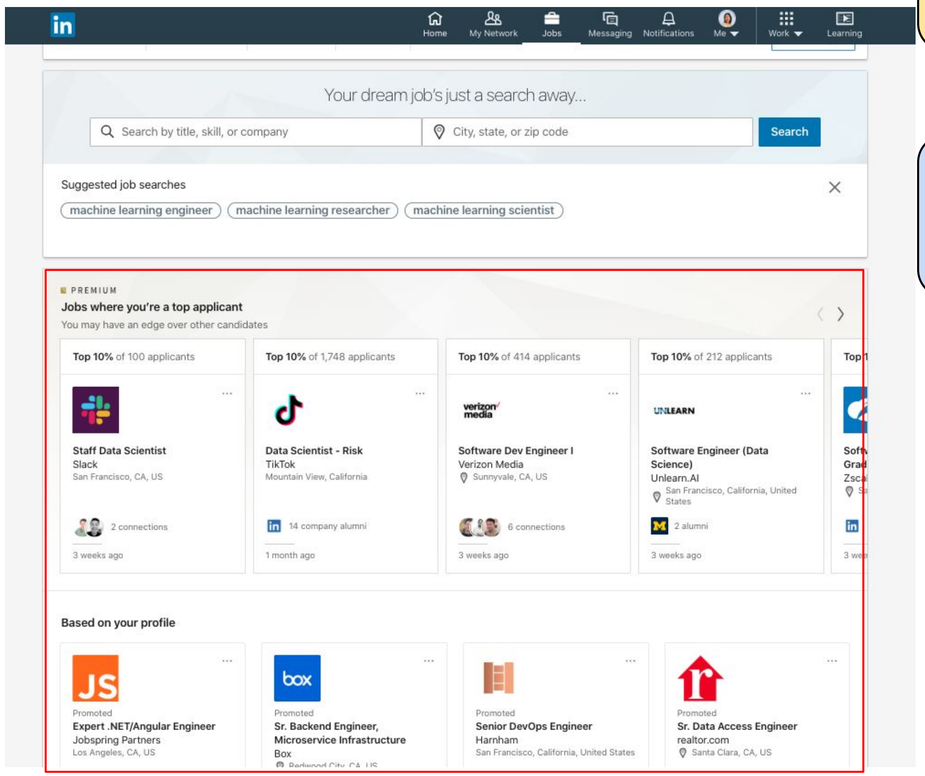
Search and Recommendation are Everywhere

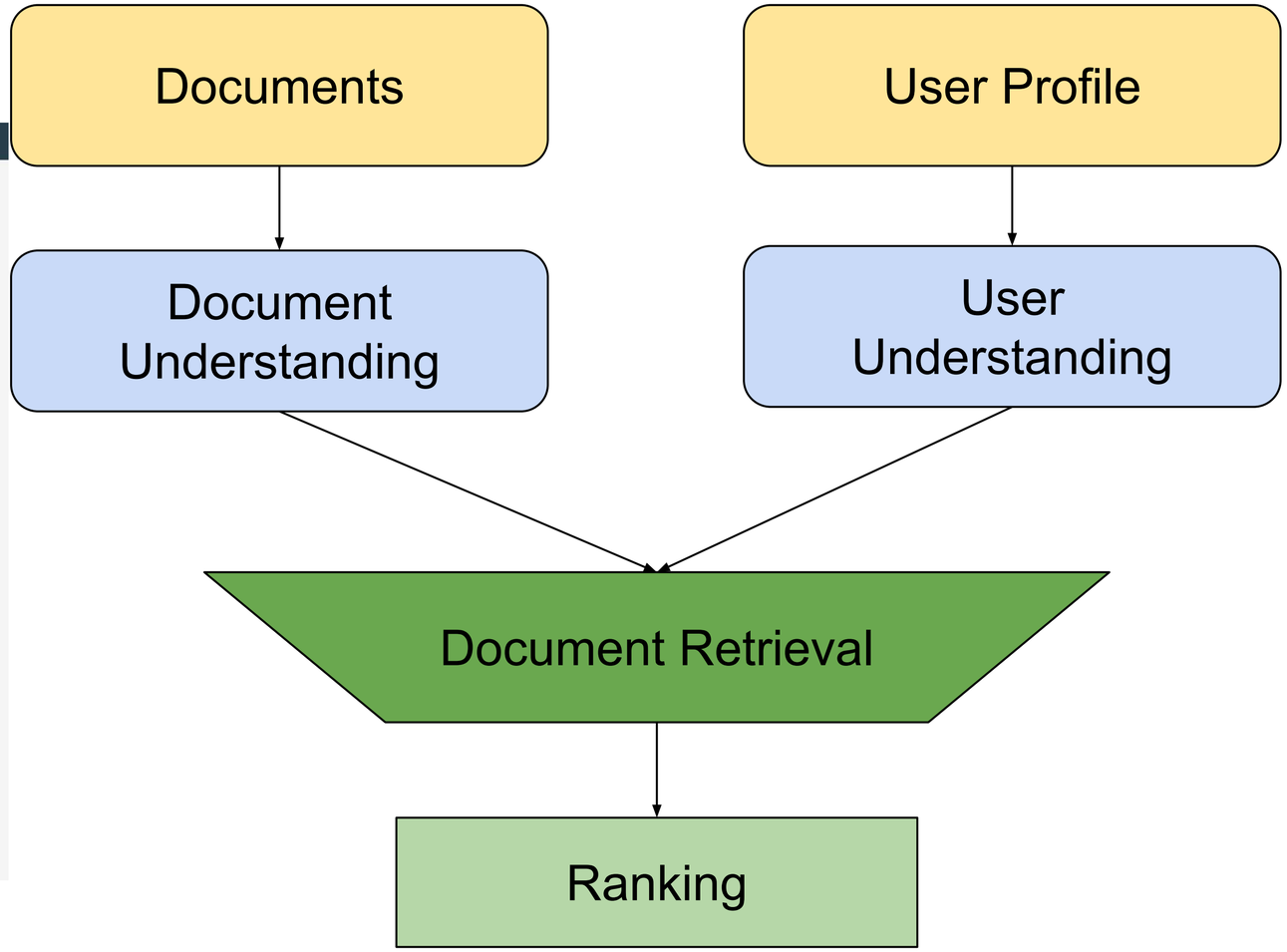
Search Systems



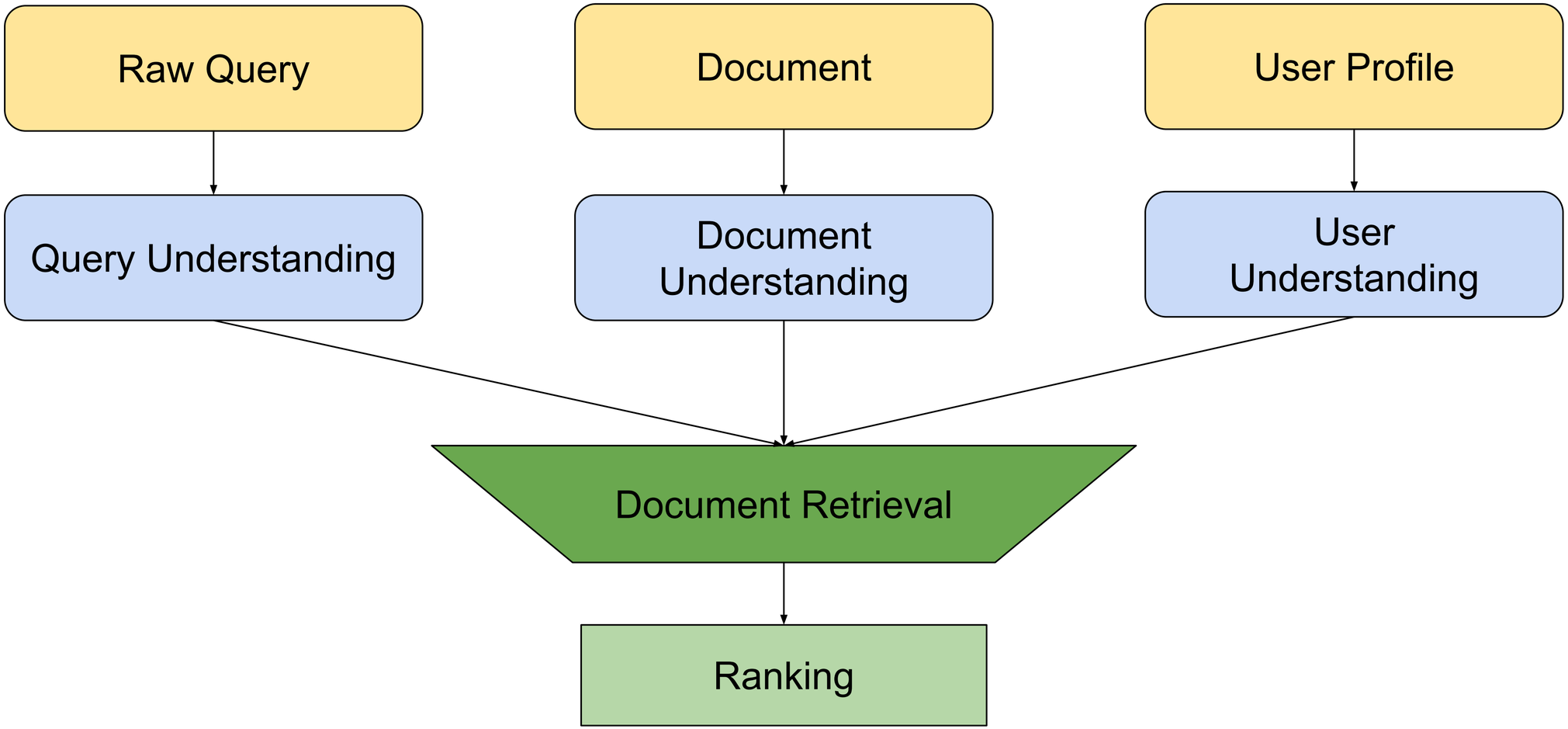


Recommender Systems

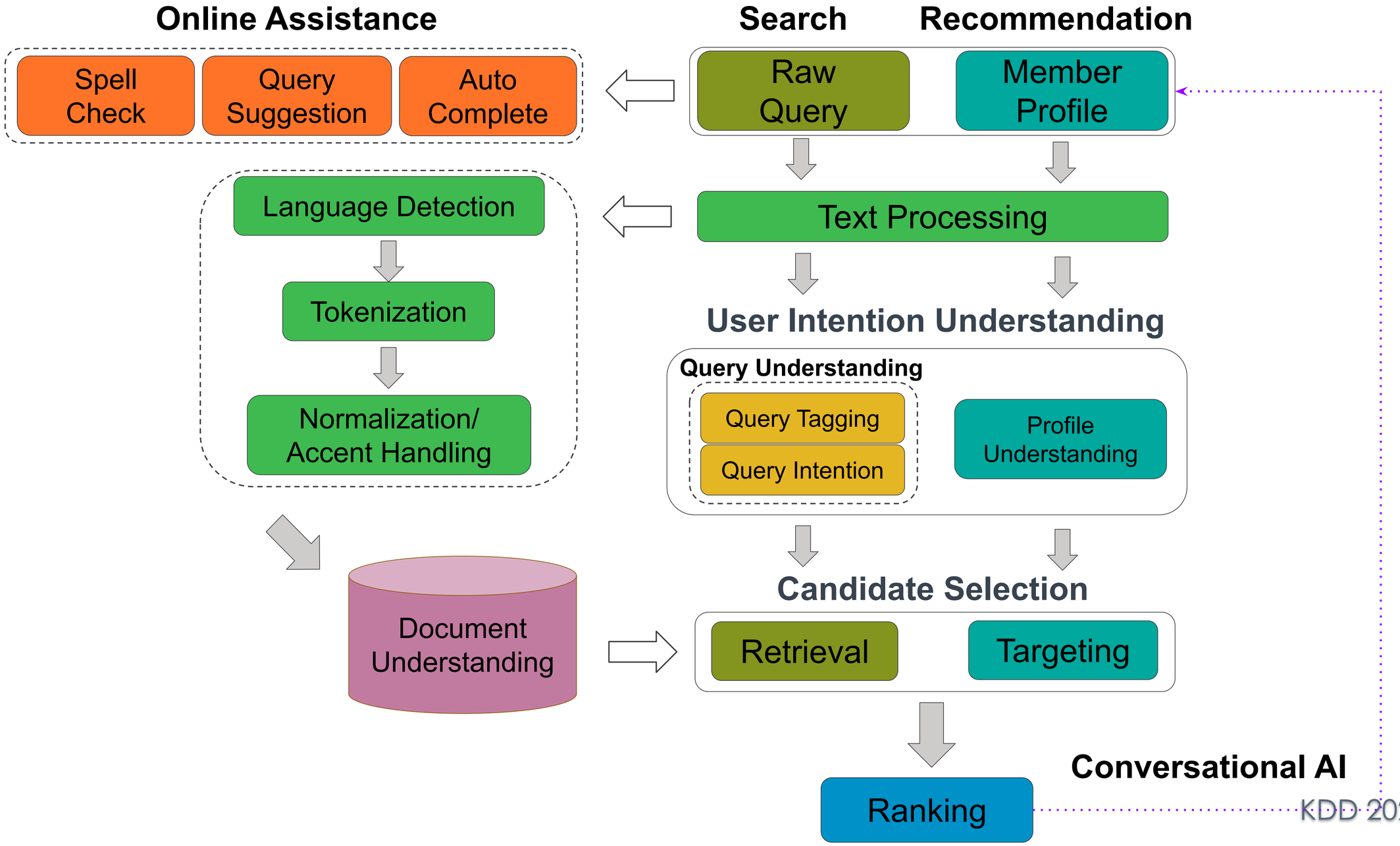




Search and Recommender Systems



LinkedIn Search & Recommendation Ecosystem



Introduction

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2 **Applications at LinkedIn**

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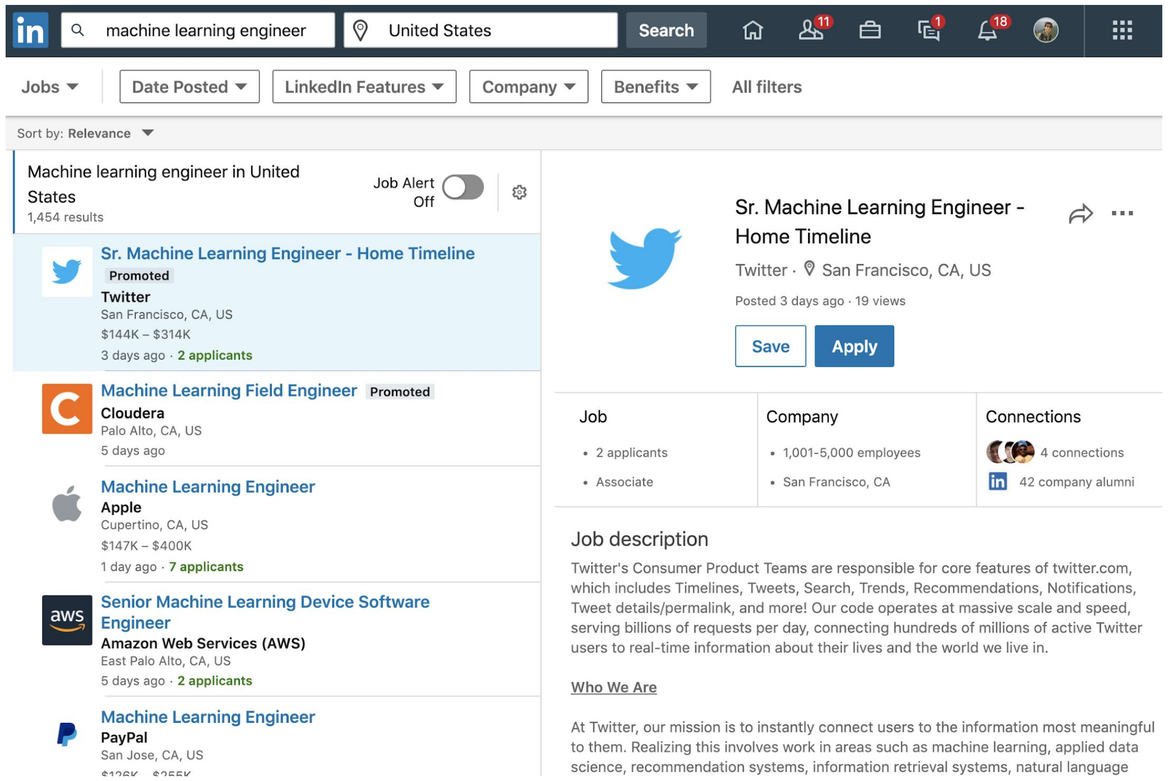
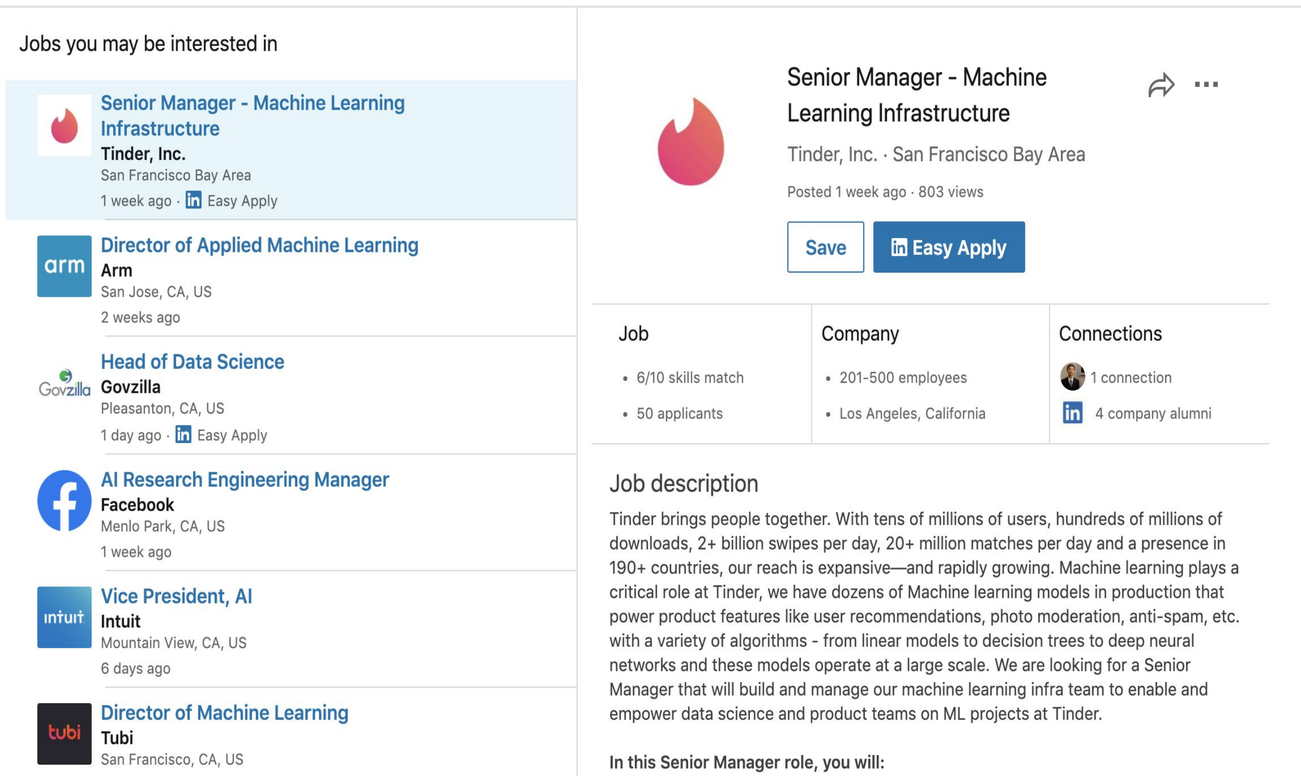
LinkedIn Search and Recommender Systems

Job Search



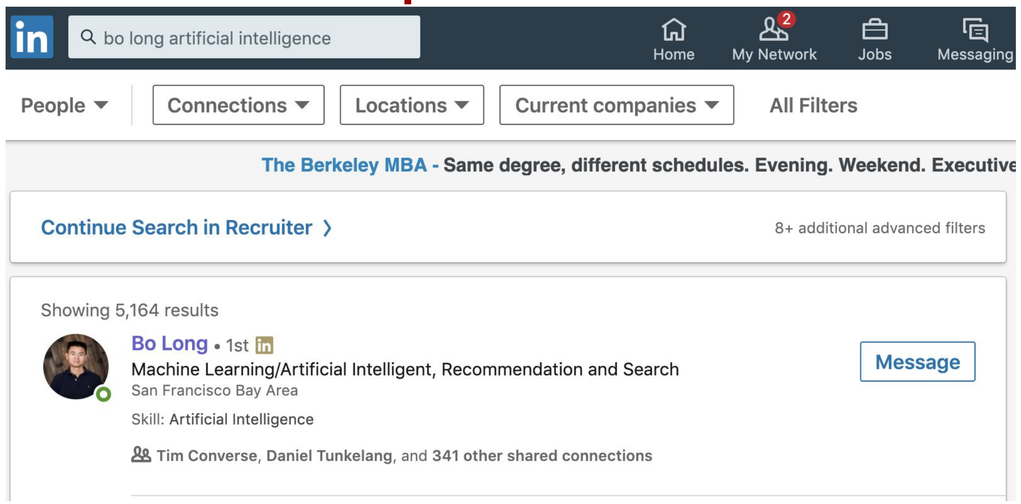
Job Recommendation



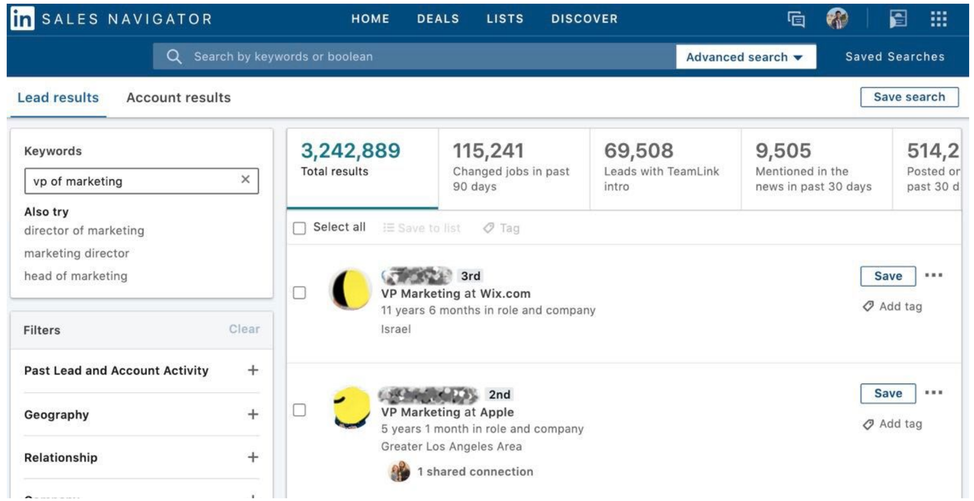
Rank job posts for LinkedIn member to help the user to find jobs that he/she would like to apply for (then, click the “apply” button)

LinkedIn Search and Recommender Systems

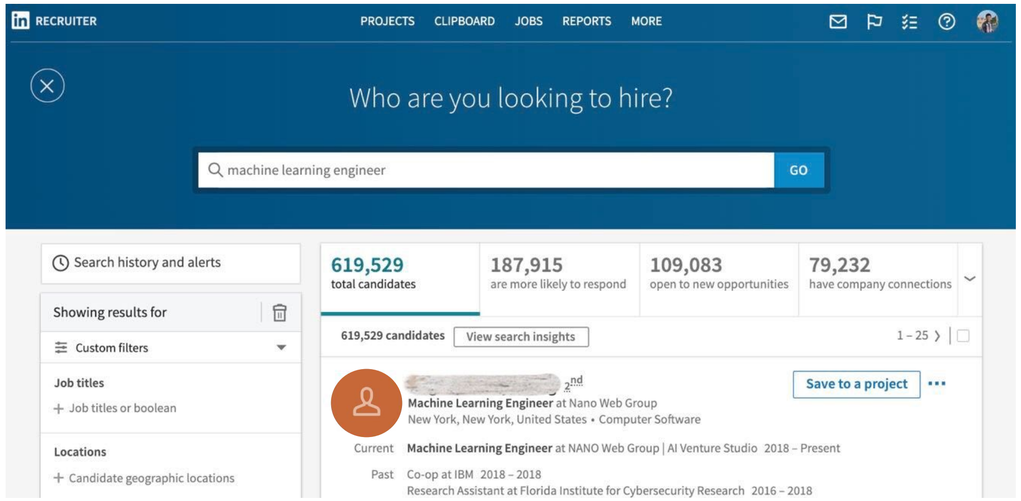
People Search



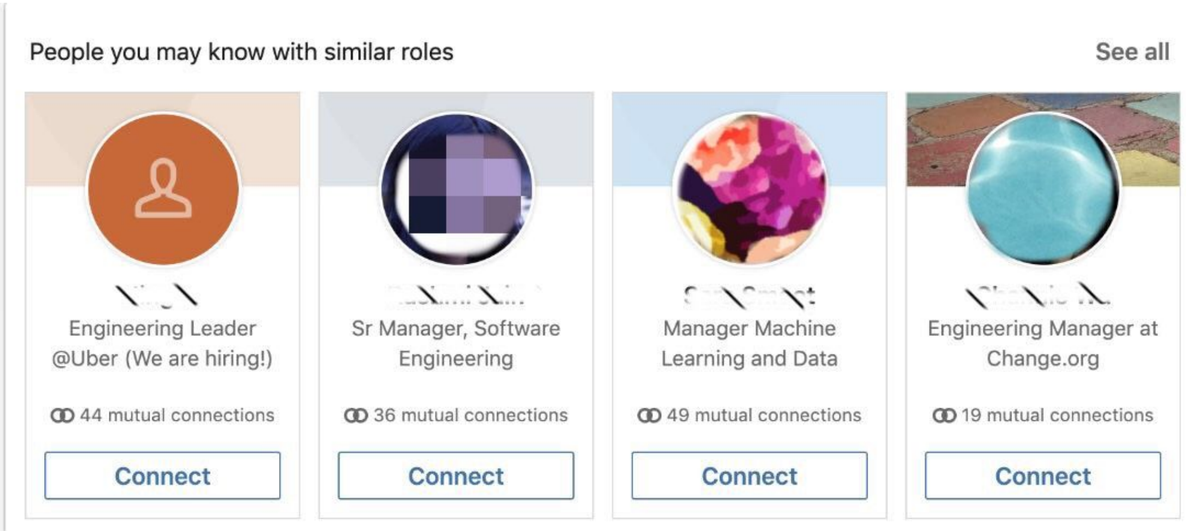
Lead Search



Recruiter Search



People Recommendation



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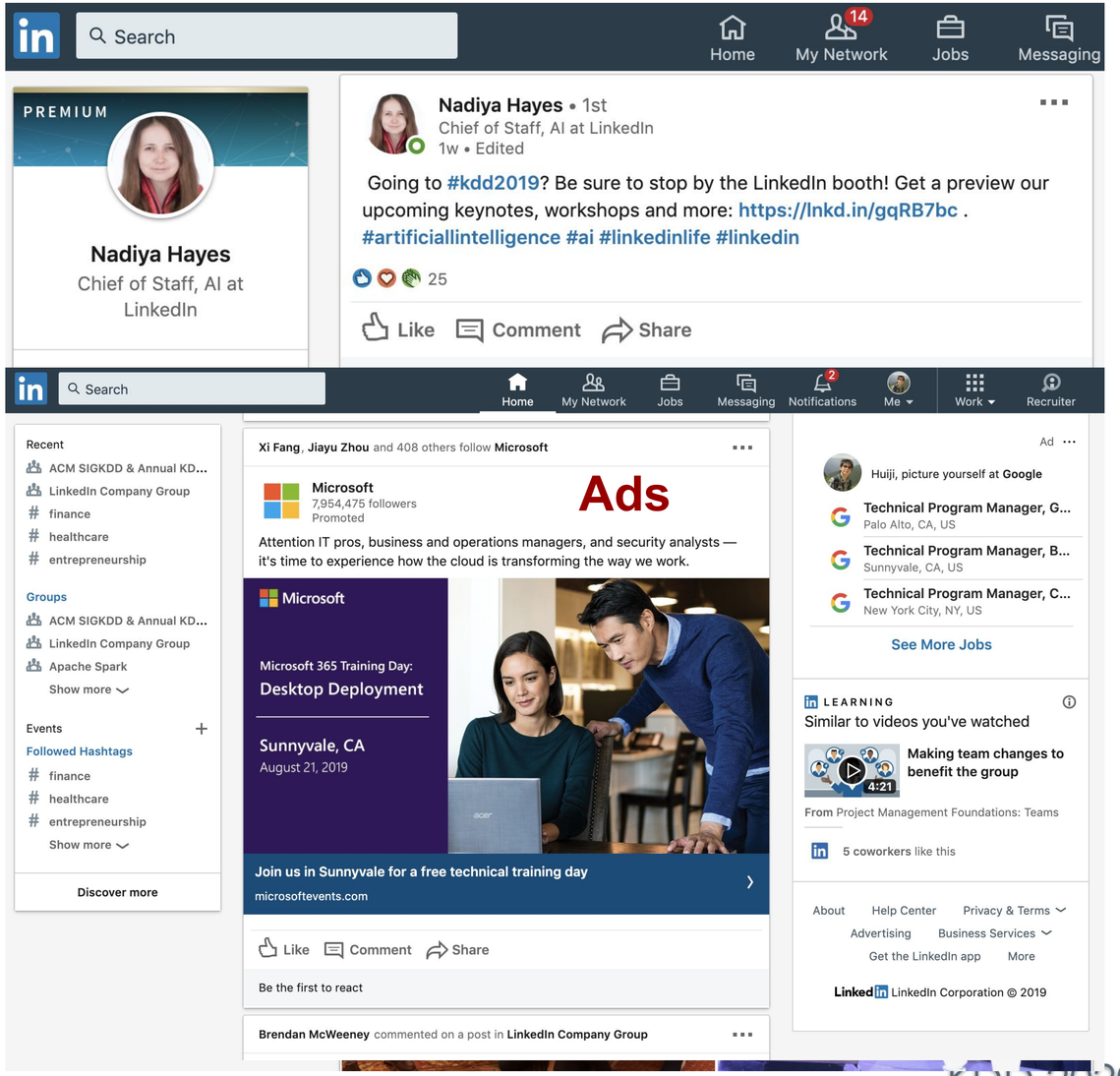
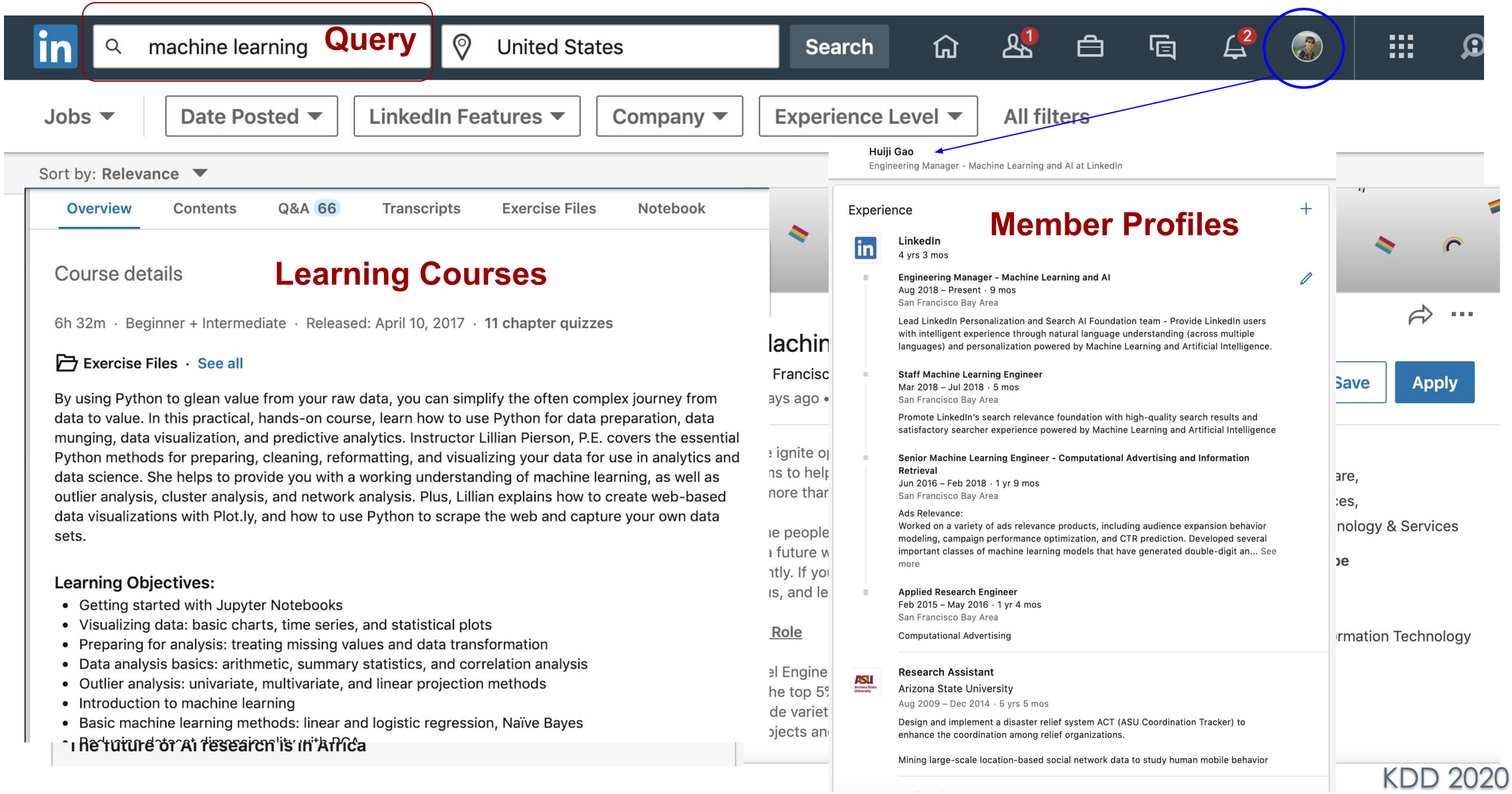
LinkedIn Search and Recommender Systems

Content Search

Content Recommendation



LinkedIn Search and Recommender Systems



Opportunities -
Deep Learning for Search and Recommender Systems

Why Deep Learning?

- **Deep Semantics** from High Dimension and Sparse Data
  - Synonymous, Disambiguation, etc.

- **Easy Feature Engineering**
  - Hand Crafted Features V.S. Auto Feature Representation

- **Model Flexibility**
  - Model end-to-end process
  - Various NN components to model and cooperate systematically

- **Multi-level Feature Representation**
  - Hierarchical Representations
    character -> token -> word -> phrase -> sentence

[Young et. al. 2018]

Applying Deep Learning in LinkedIn Search & Recommendation

- **Feature Driven**
  - Representation Learning
    - Using features generated from deep learning models

      e.g., word embedding

- **Model Driven**
  - Power product features directly with deep learning models
    - CNN/LSTM/Seq2seq/GAN/BERT based deep NLP models

Applying Deep Learning in LinkedIn Search & Recommendation

- Offline

People Search (NDCG@10)		**Job Search (NDCG@10)**	**Ads Click-through Rate (AUC)**	**Ads Conversion (AUC)**
Wide Features	-	-	-	-
CNN	+1.32%	+2.36%	+3.43%	+1.37%
LinkedIn BERT	+1.98%	+5.14%	-	-

- Online (CNN)
  - **Job Search**
    - Job apply clicks: **+1.62%**
    - Onsite paid applicants: **+1.38%**
  - **People Search**
    - Satisfied clicks: **+0.78%**
    - Successful sessions: **+0.37%**

Applying Deep Learning in LinkedIn Search & Recommendation

Query Suggestion - english market

No Personalization

Coverage: +80% Impressions, +26% CTR

+1% Total job application

With Personalization

+1.18% Session Success for passive job seekers

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Major Components of a Search/Recommender System

1.Query & User Understanding

A query or a userprofile are processed so that the systems can use the processed information in the other components

2. Candidate Retrieval

Retrieve all the relevant items to the user or query with high recall

3. Learning to Rank

Rank the items by the order of the relevance to the user's intent or the query with high precision

Query and User Understanding

- Query and user understanding provides personalization features for candidate retrieval and ranking.
- Infer the intent of a user by extracting semantic meaning from the query and other information.

Candidate Retrieval

- Syntactic retrieval
  - based on string matching
  - use inverted index
  - can include different fields
- Semantic retrieval
  - based on vector space representation.
  - approximate nearest neighbor search

Learning to Rank

- Ranking strategies: point-, pair- and list-wise.
- Common networks: Siamese, Interaction-based, Wide & Deep.

Handson Sessions

1.Query & User Understanding

- Intent Classification
  - CNN with DeText
- Query Auto Completion
  - Incomplete User Input
  - Suggest completions that save keystrokes

2. Candidate Retrieval

- ElasticSearch
- Embedding Based Retrieval
- ANN Algorithms
  - LSH
  - IVFPQ
  - HNSW

3. Learning to Rank

- GLMix & GDMix
- Global Effect
  - Linear Models
  - DeText
- Random Effect
  - Large Scale Linear Models

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Query & User Understanding

Weiwei Guo

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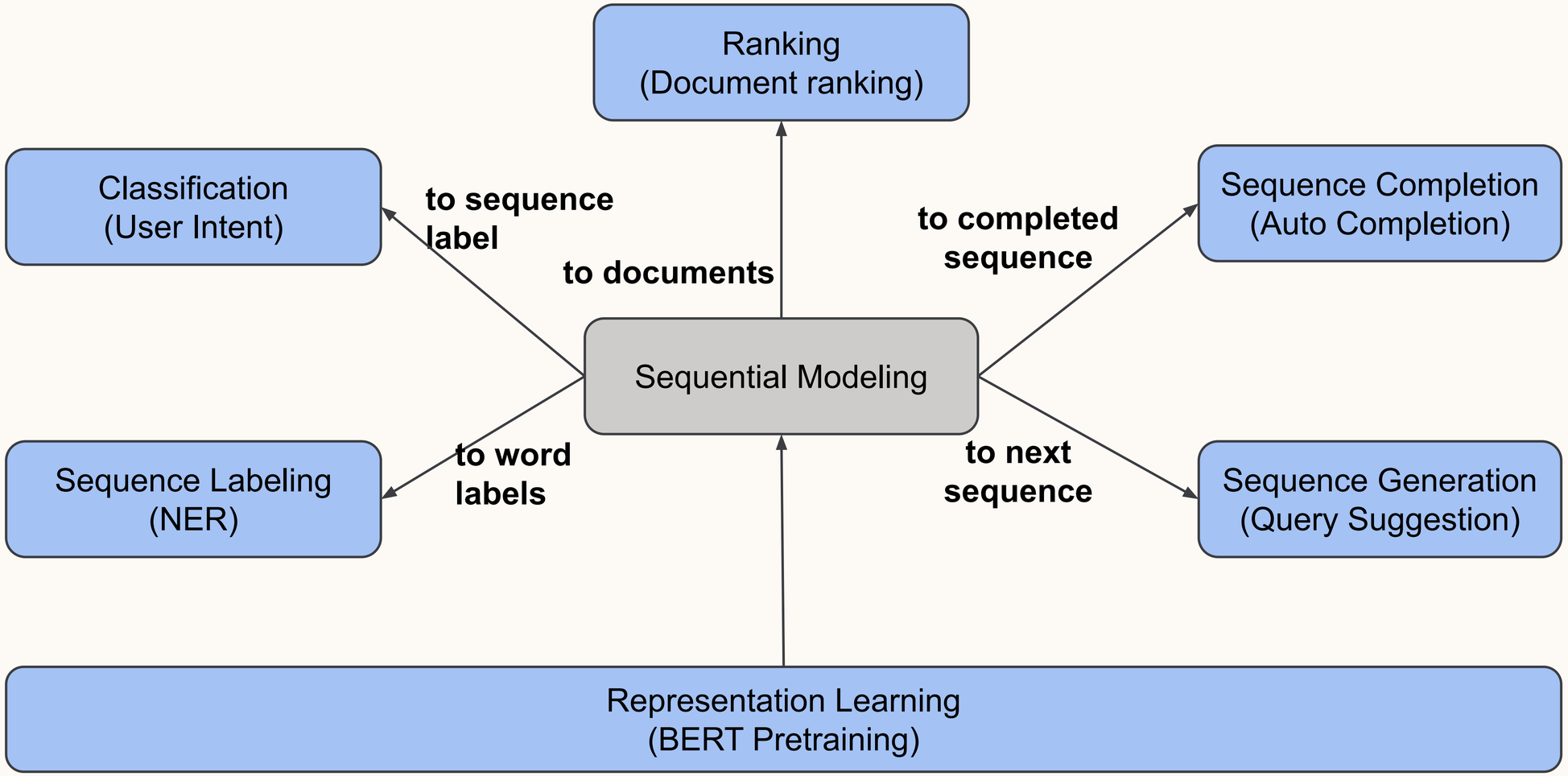
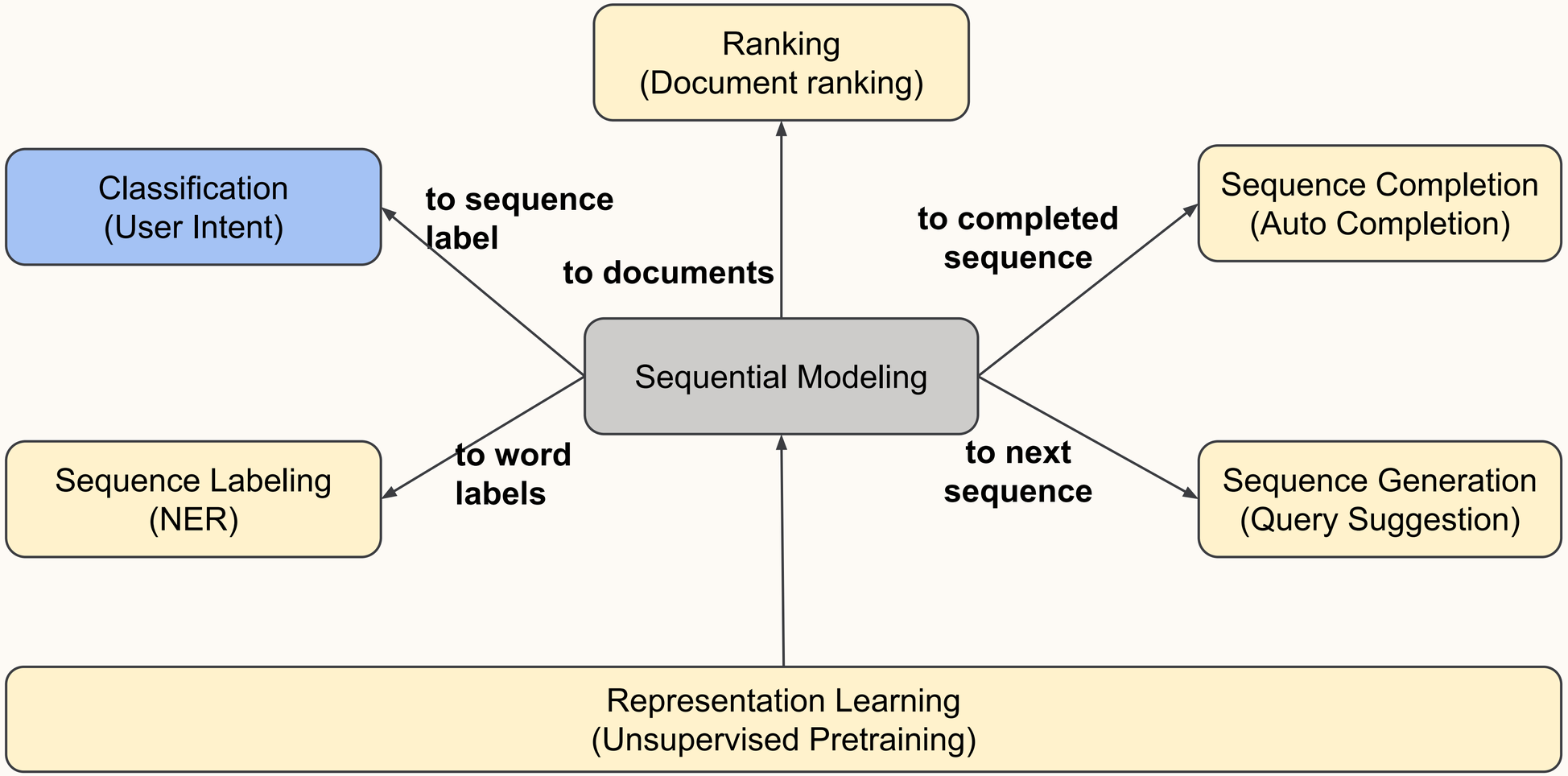
Query and User Understanding

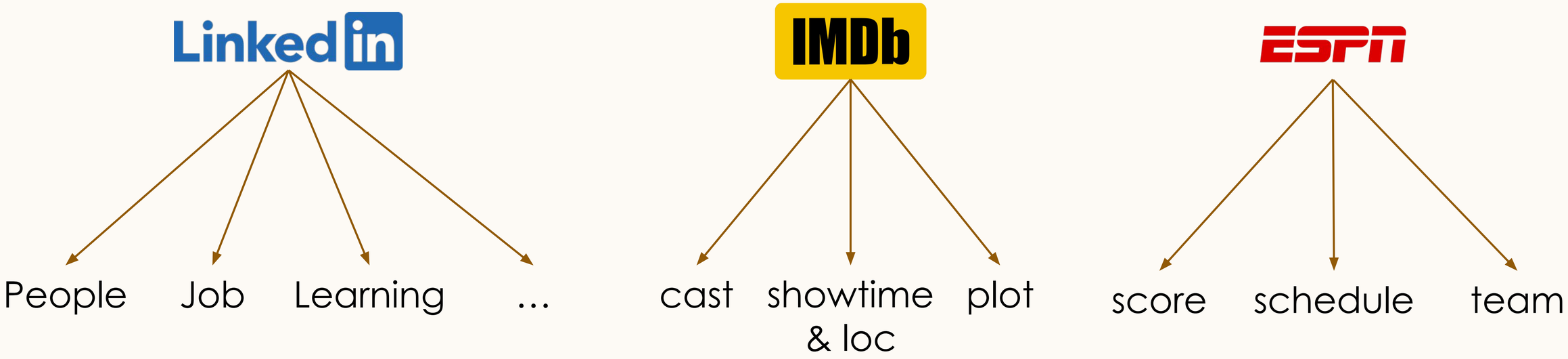


Query and User Understanding



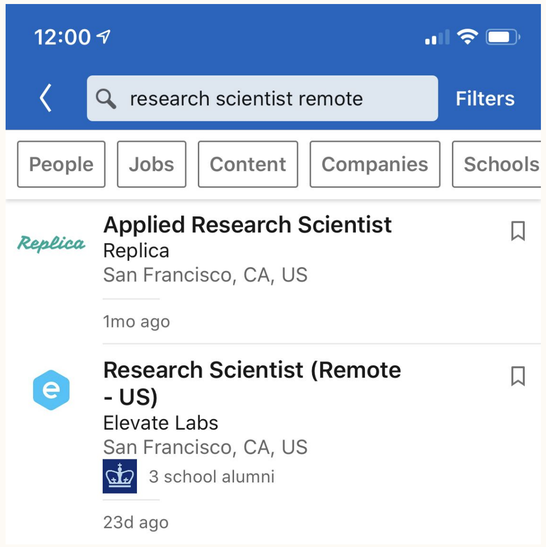
User Intent

Task: Identifying what information the user is looking for

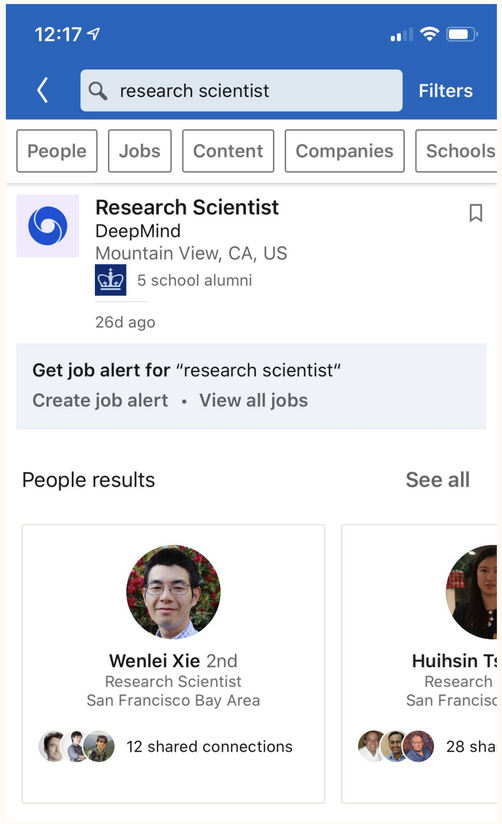


User Intent - Application

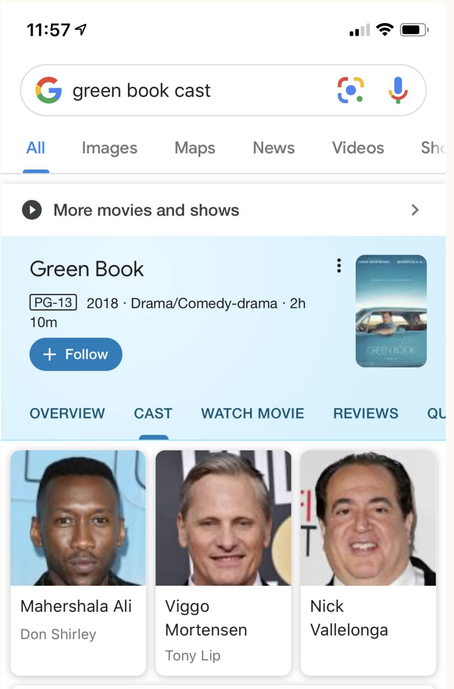
Identify Search Vertical



Search Result Ranking/Blending



triggering QA



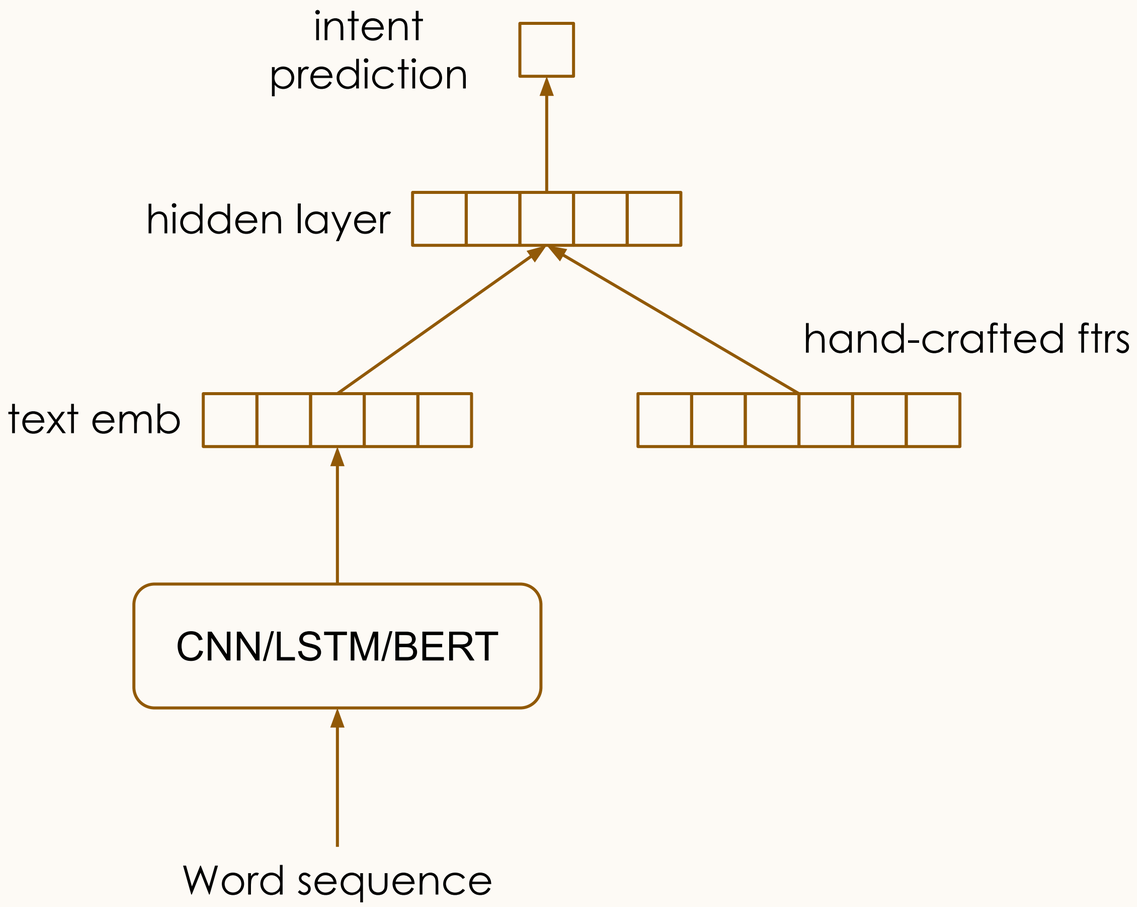
Approach: Text Classification

- Traditional Methods
  - Features: Bag-of-words, n-gram, etc
  - Models: Logistic Regression, naive bayes, SVM

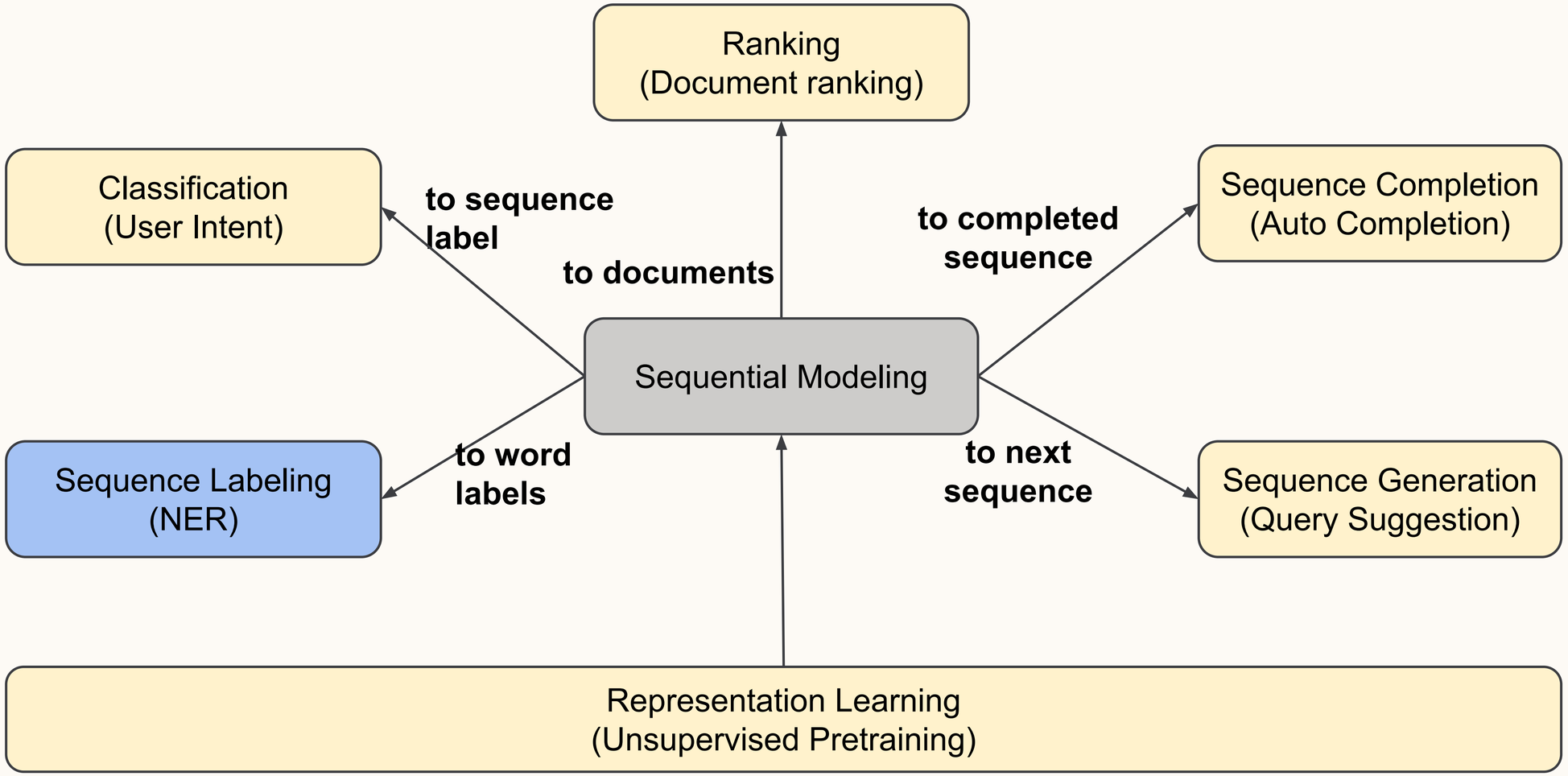
- Deep Learning Methods
  - Word embedding + linear classifier (FastText)/CNN/LSTM/Transformer/...

Deep Learning Approaches

(Kim 2014, Hashemi et al. 2016, Liu et al. 2020)



Query and User Understanding



Sequence Labeling - Task

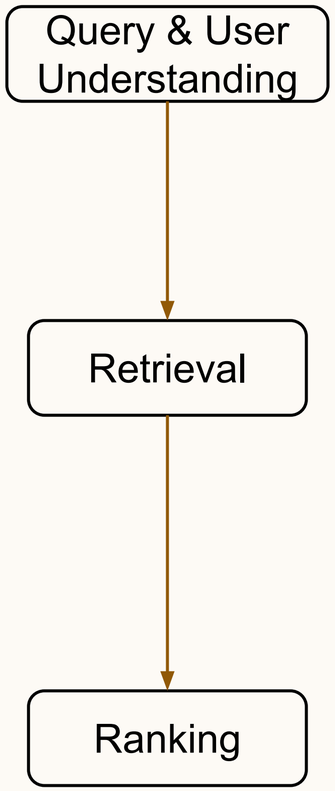
- Document understanding

Washington D.C. was named after George Washington.
LOCATION PERSON

- Query understanding

pinterest program manager
COMPANY TITLE

Sequence Labeling - Application

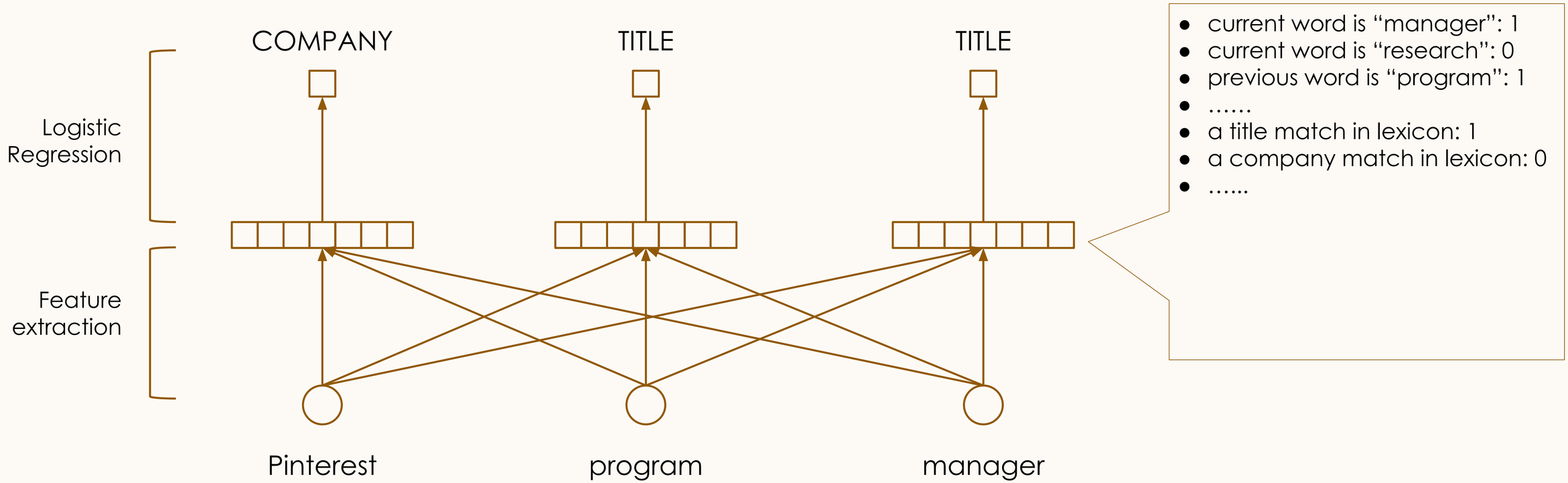


- Ignore the unimportant words
  - "looking for a ***research scientist*** job"

- Extracting keywords from documents
- Resolve ambiguity
  - sap (company vs skill)

Sequence Labeling - Approach

Classification on each word

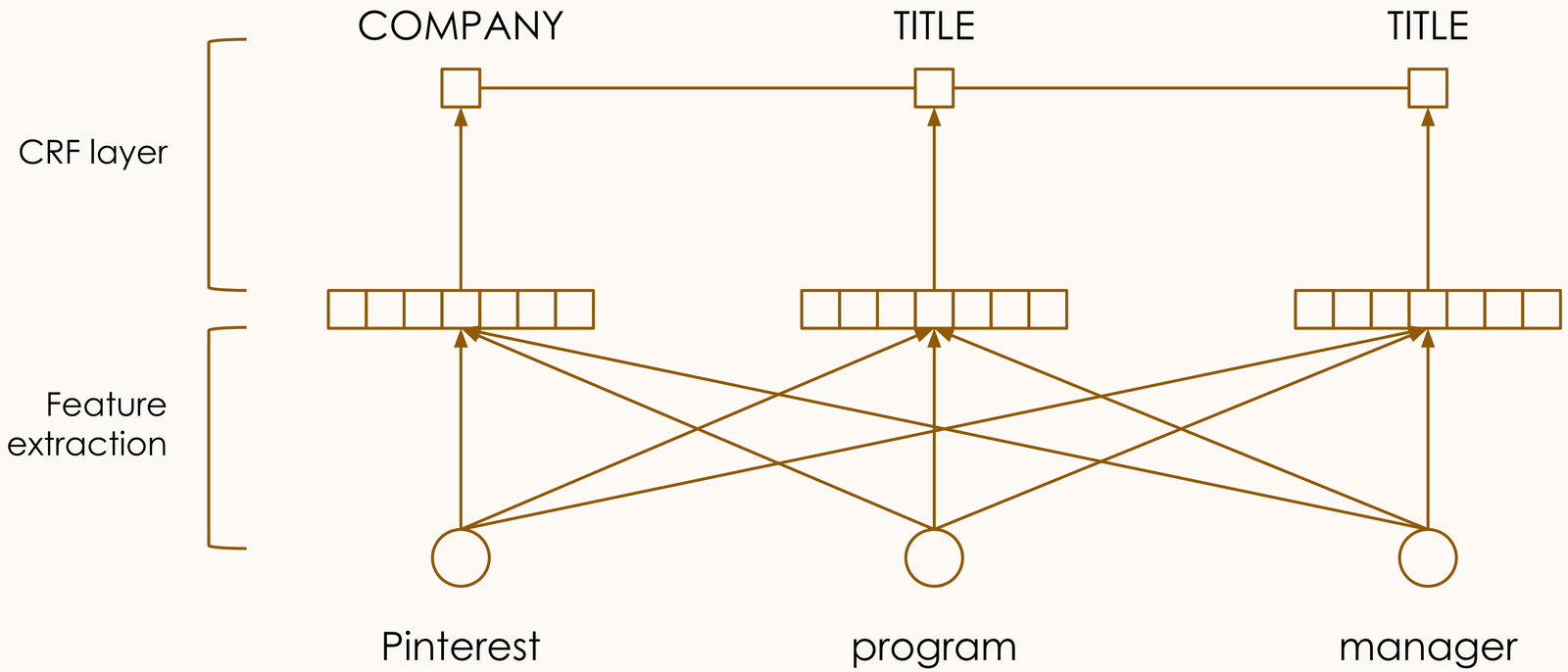


- Cons: Ignore the word label relations

Sequence Labeling - Approach

(Lafferty et al. 2001)

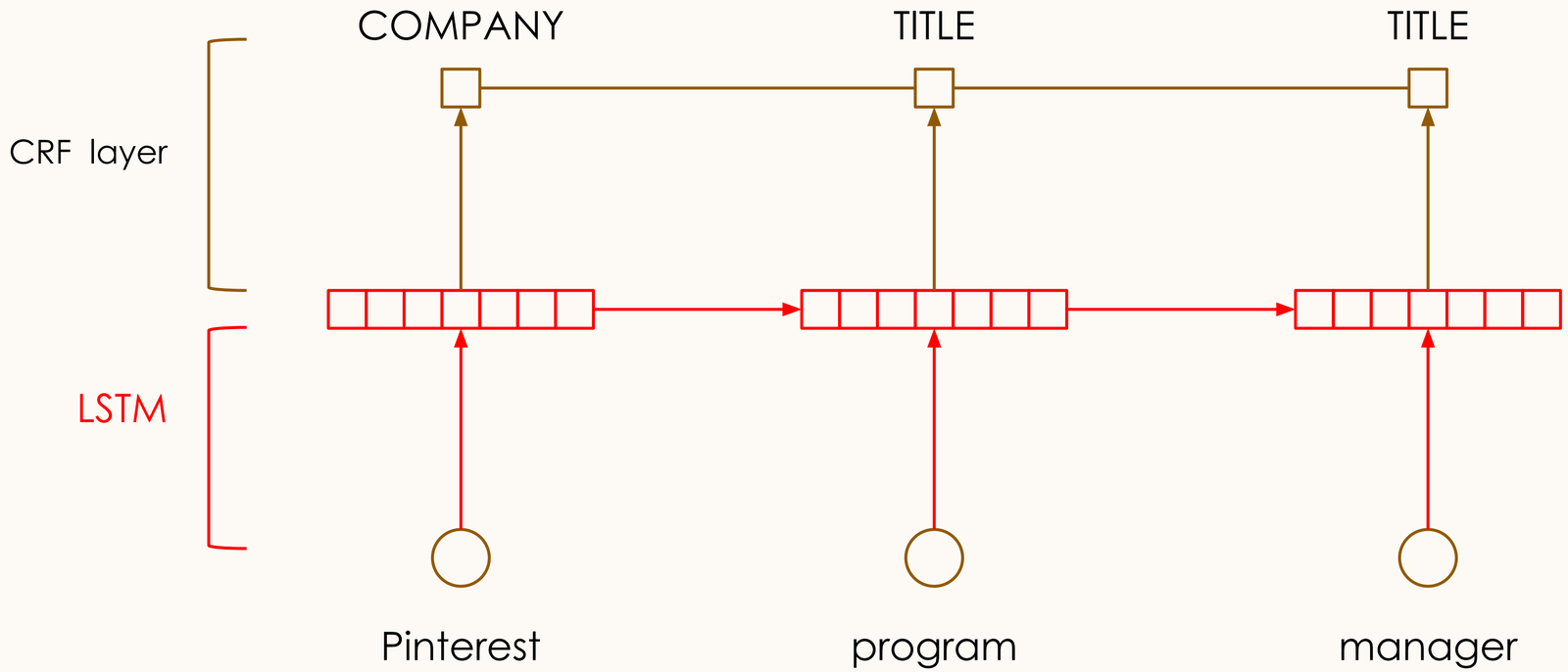
Conditional Random Field: Sequential prediction



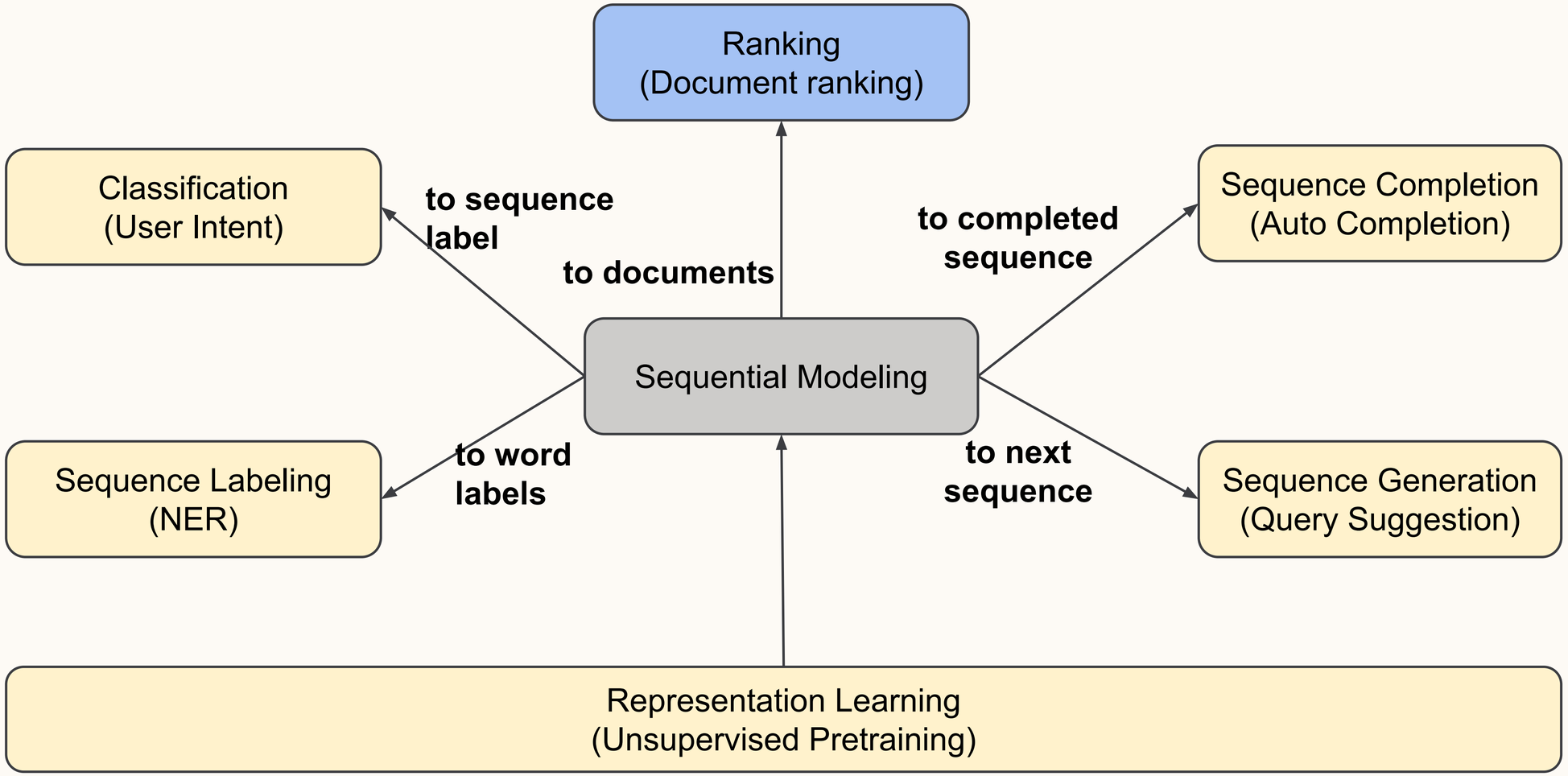
Sequence Labeling - Approach

(Huang et al. 2015, Ma & Hovy 2015)

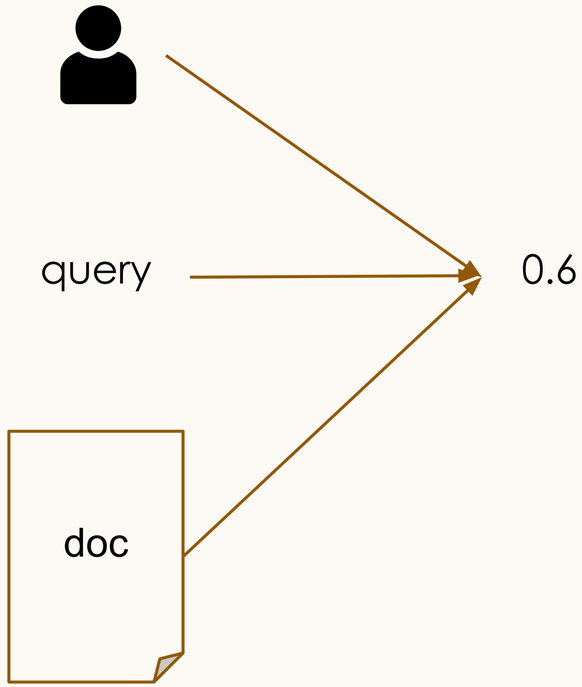
Deep learning approach: extracting powerful contextual features



Query and User Understanding



Ranking - Task

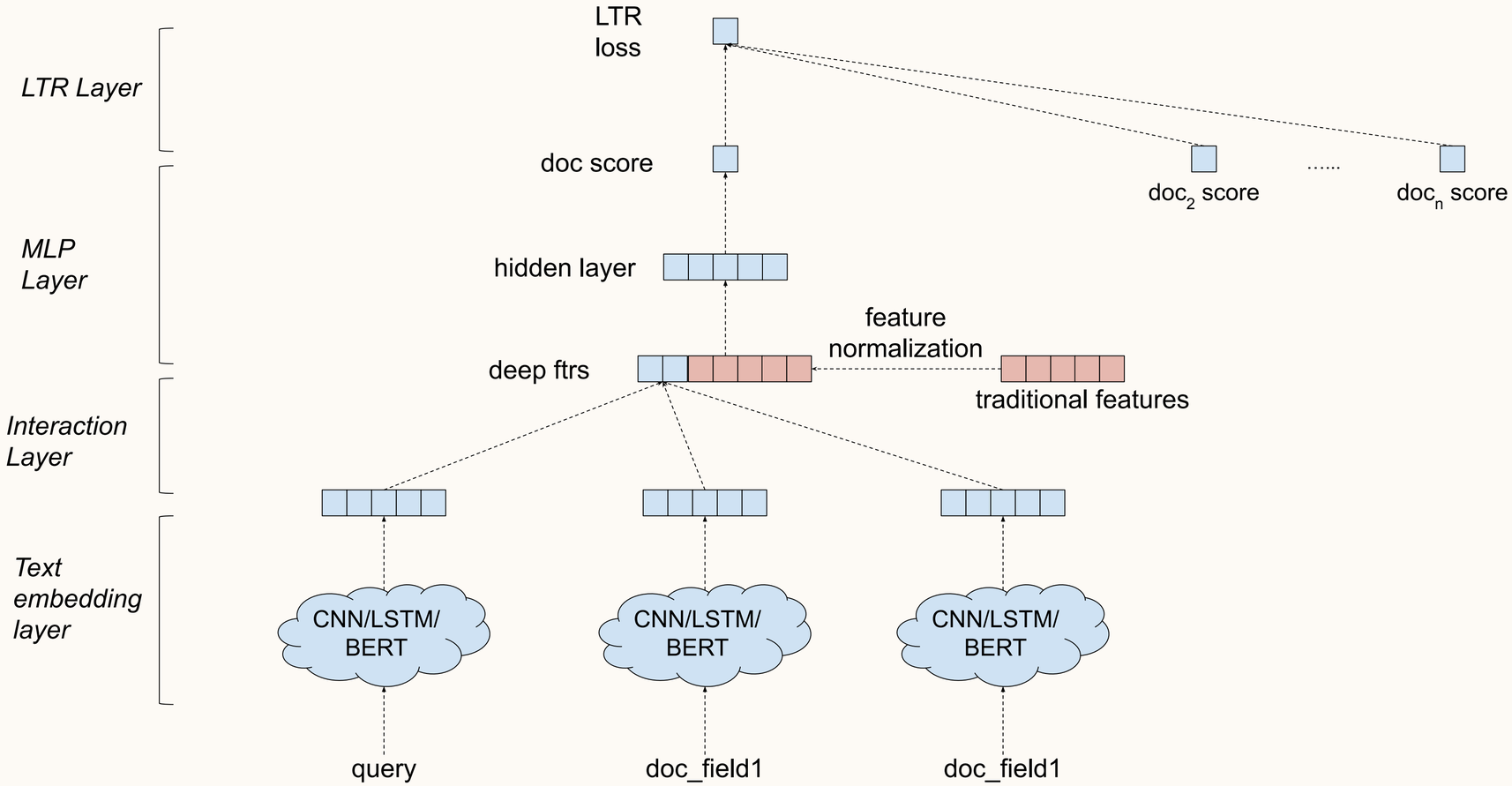


Ranking - Traditional Methods

- Hand-crafted features
  - Query/user/document matching features
    - Cosine similarity between query and doc title
    - Clickthrough rate from query to this doc based on search log
    - ……..
  - Document alone
    - popularity
    - number of incoming links
    - …….

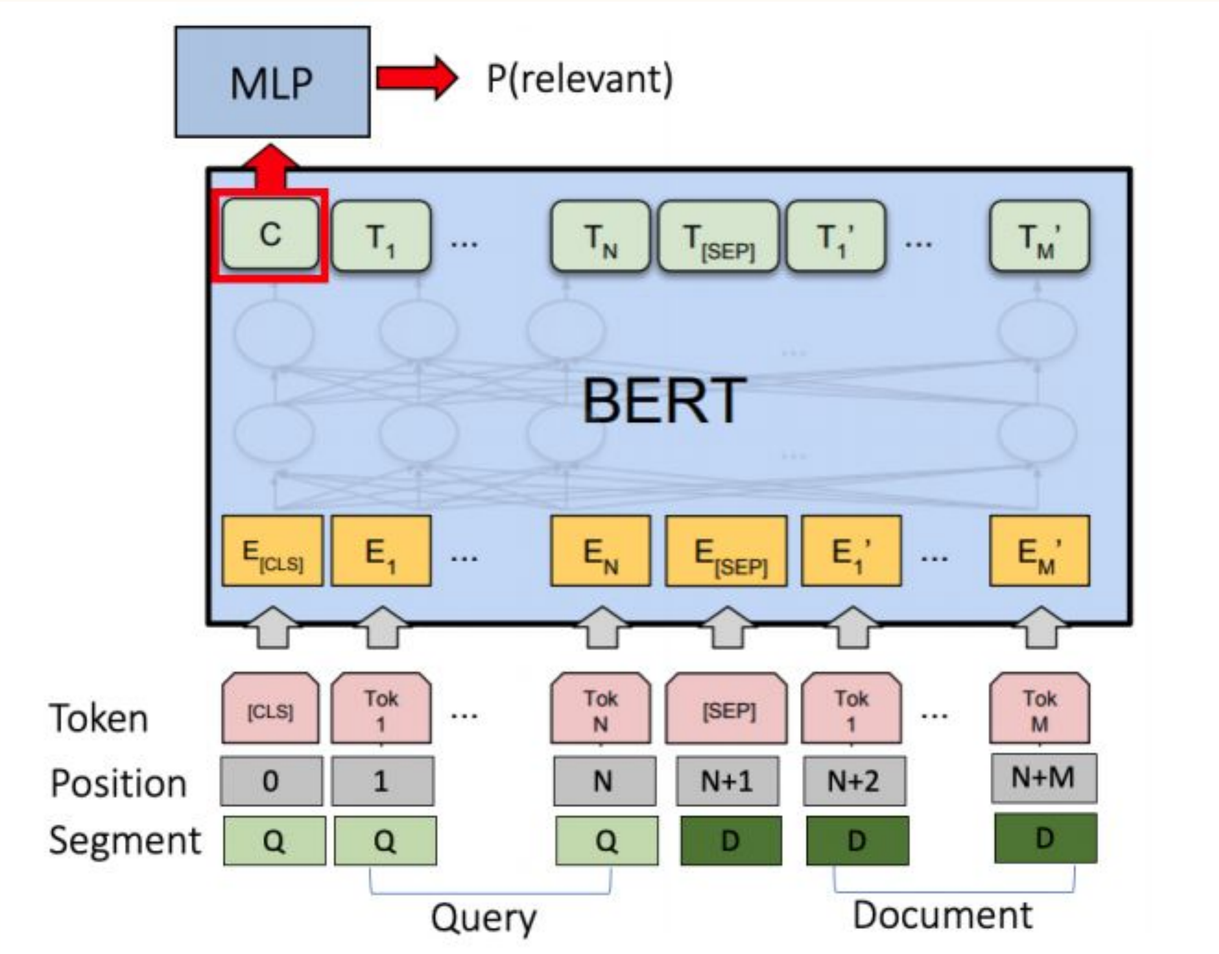
Ranking - Representation based Methods

Guo et al. 2020



Ranking - Interaction based Methods

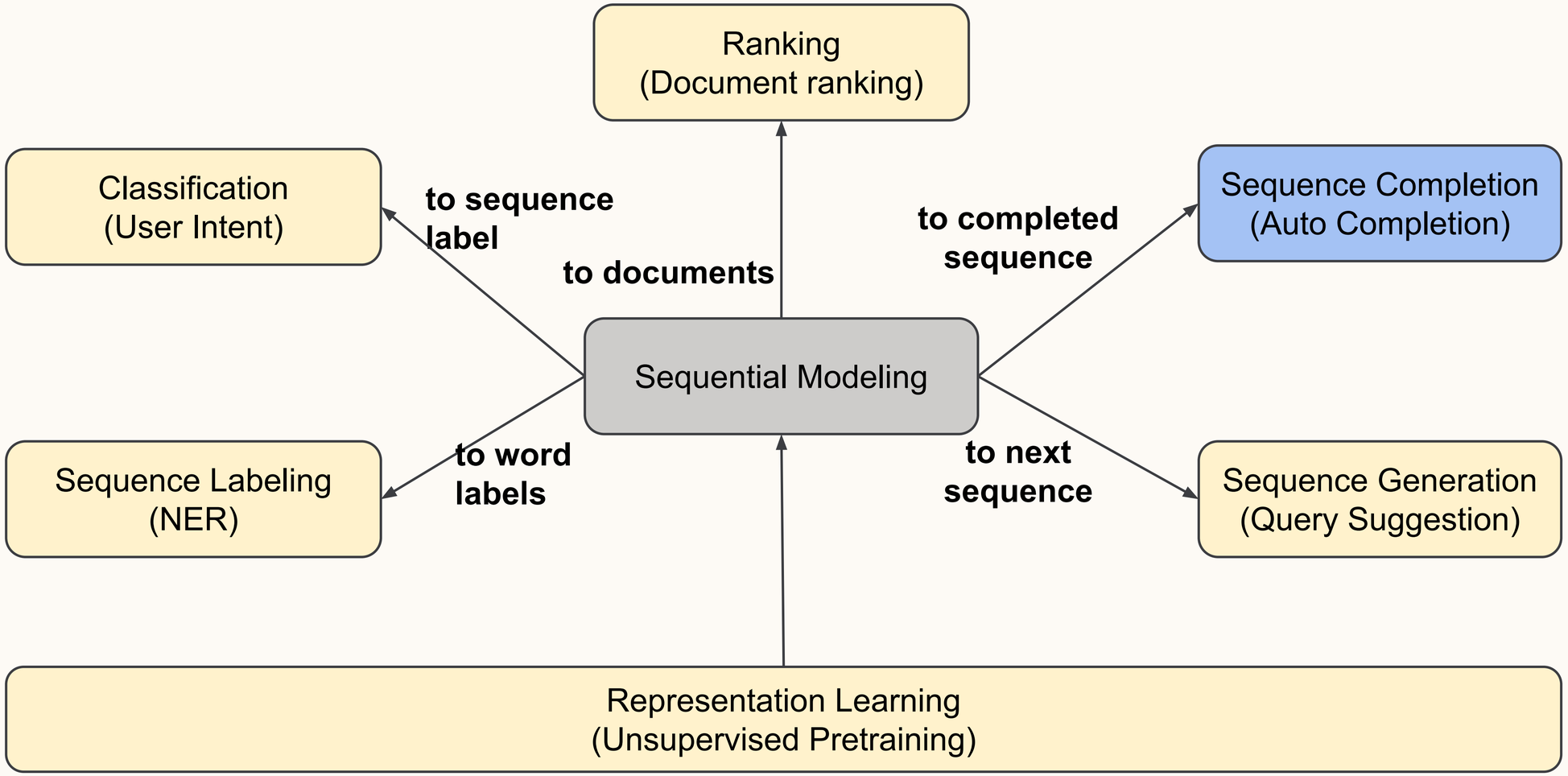
(Dai & Callan 2019)



Ranking - Comparison

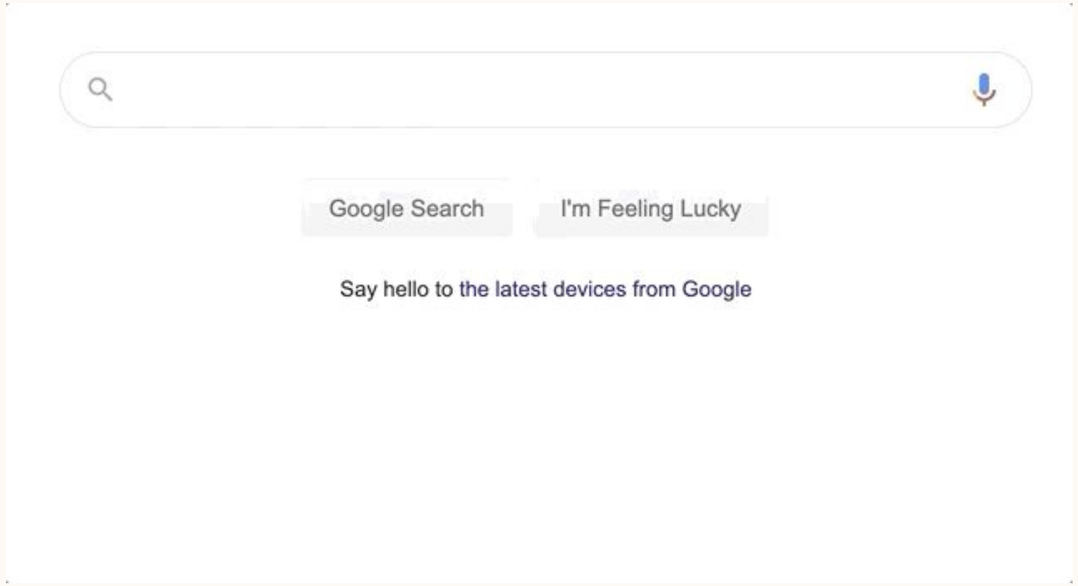
	Representation based	**Interaction based**
interaction between query and docs	word-level	text-level
Relevance	-	Better
Doc precomputing	✔️	❌

Query and User Understanding

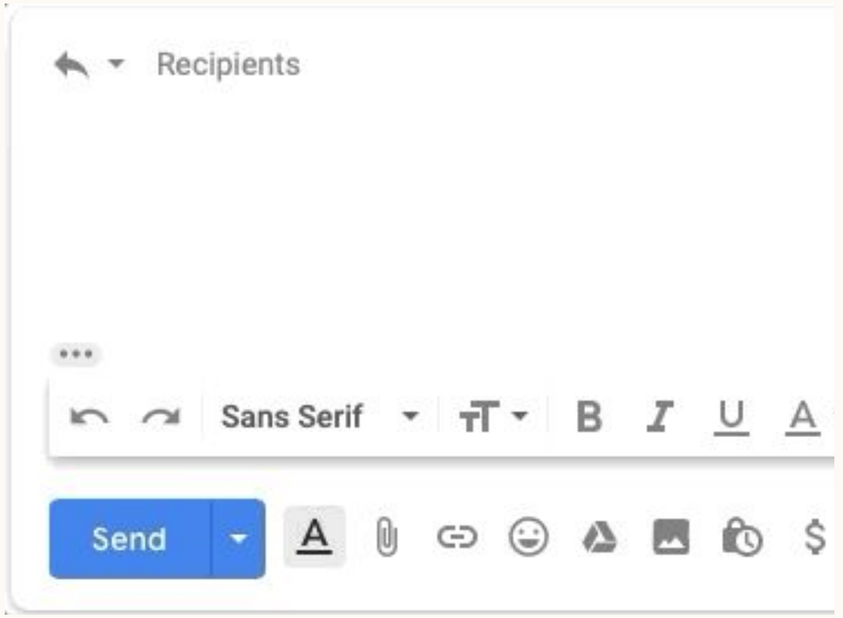


Sequence Completion - Task

On queries



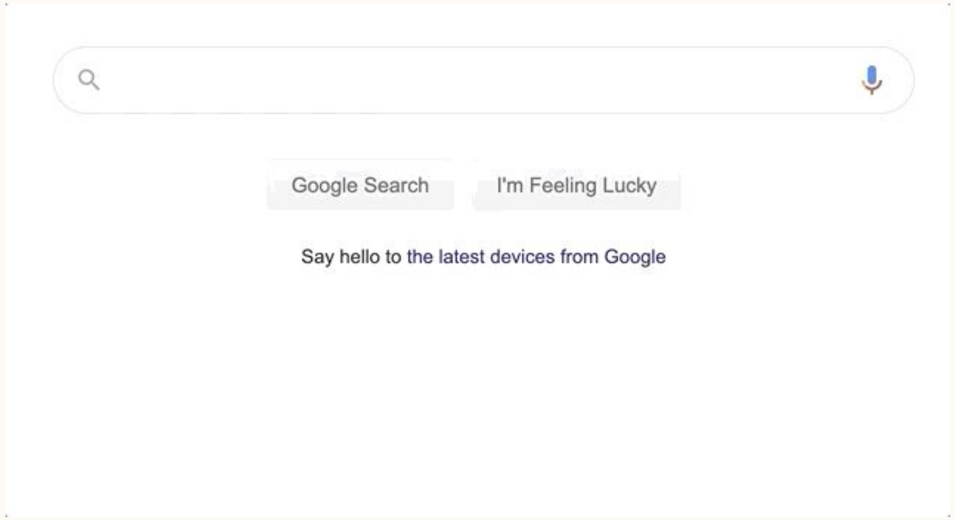
On documents



Sequence Completion - Goal

Better user experience

- Speed up human-computer interaction
  - Save 35/40 = 87.5% keystrokes in the example

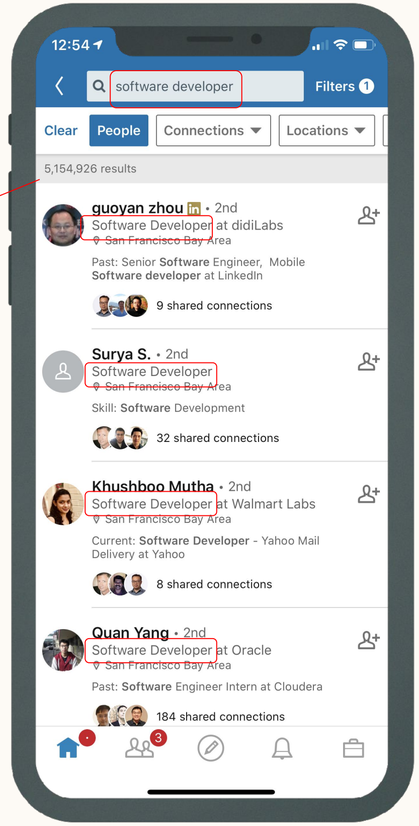


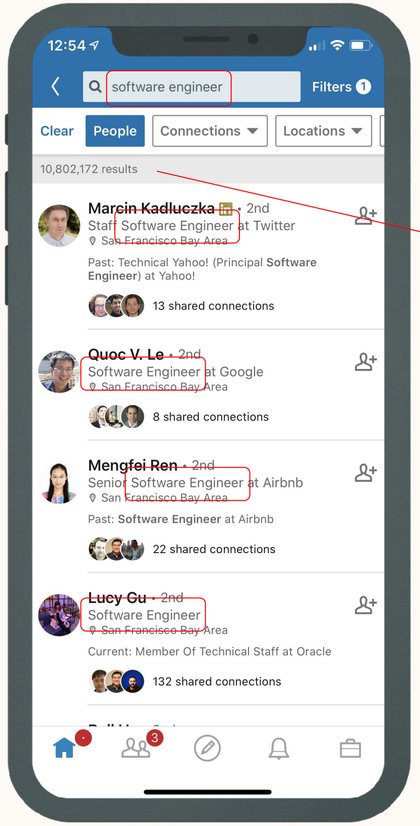
Sequence Completion - Goal

Guide Users to Better Search Results

software developer

5,154,826 results





software engineer

10,802,172 results

query prefix: ***sof***

Sequence Completion - Challenge

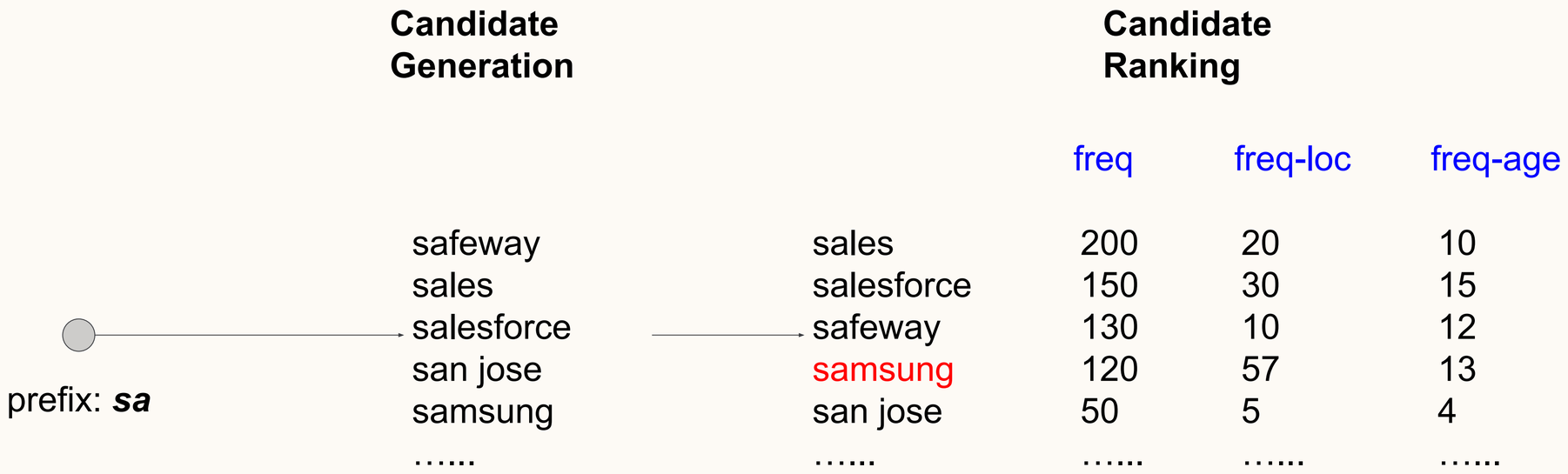
- Limited Context
  - Little information in a query prefix

- Latency
  - For each keystroke, the results need to be returned in 50ms

Sequence Completion - Traditional Methods

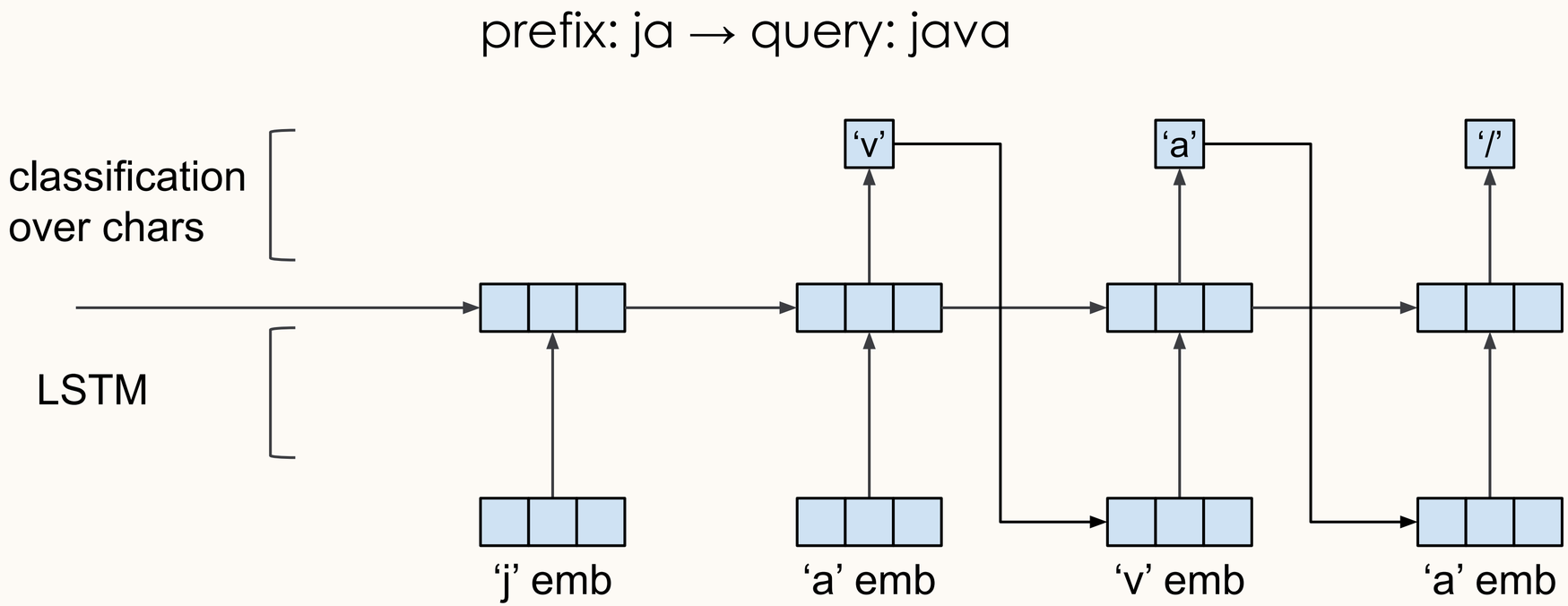
Memorizing the query frequency

(Bar-Yossef & Kraus, 2011)



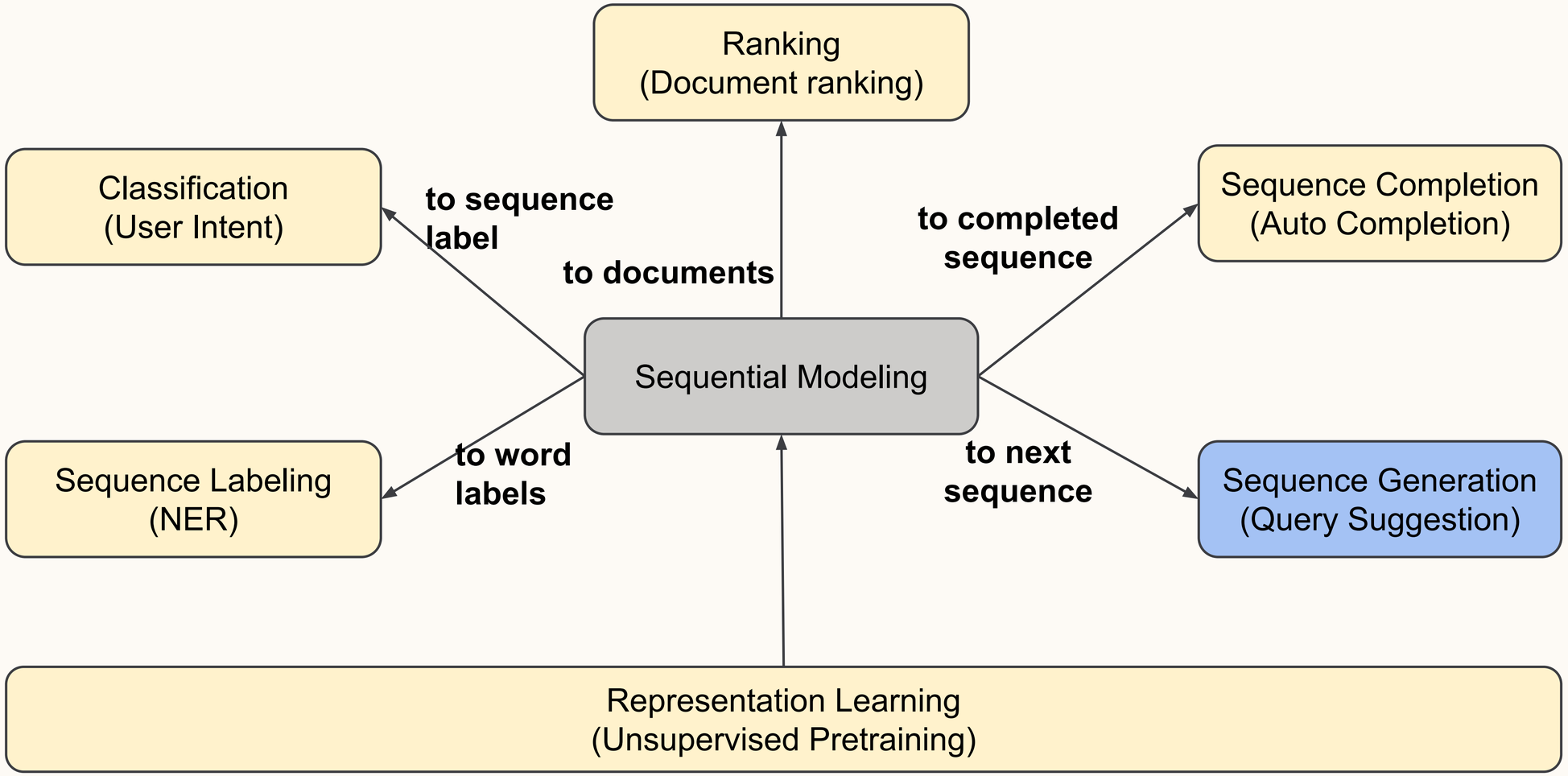
Sequence Completion: Deep Learning Approach

(Park 2017, Wang et al. 2020)



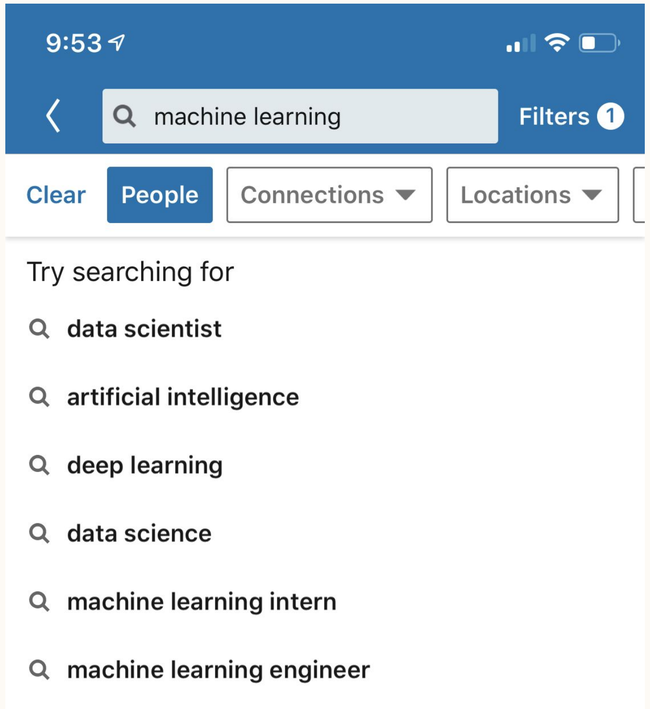
- Summarize the context by LSTM
- Generating the whole query by beam search

Query and User Understanding

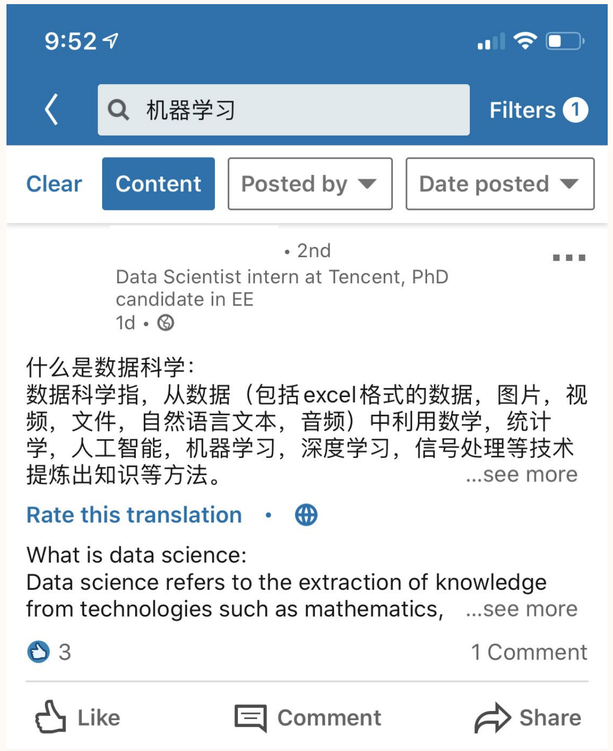


Sequence Generation - Task

Query Suggestion on queries



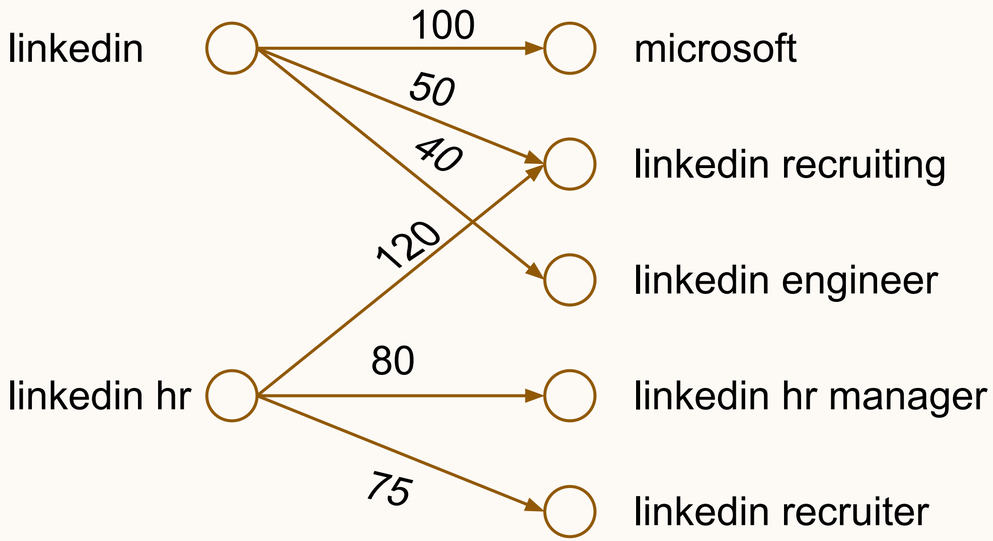
Machine Translation on documents



Sequence Generation - Traditional Methods

Based on query co-occurrence

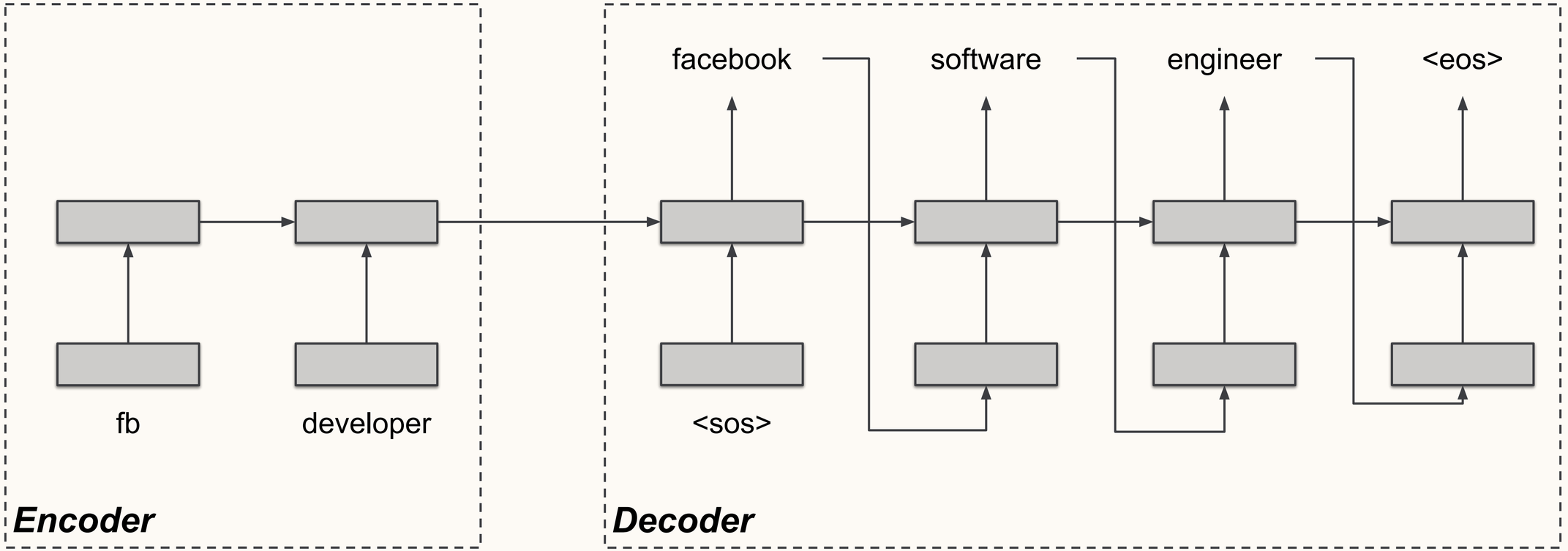
- Collaborative Filtering



- Problems
  - No word semantics understanding
  - Cannot handle new queries

Sequence Generation - Deep Learning

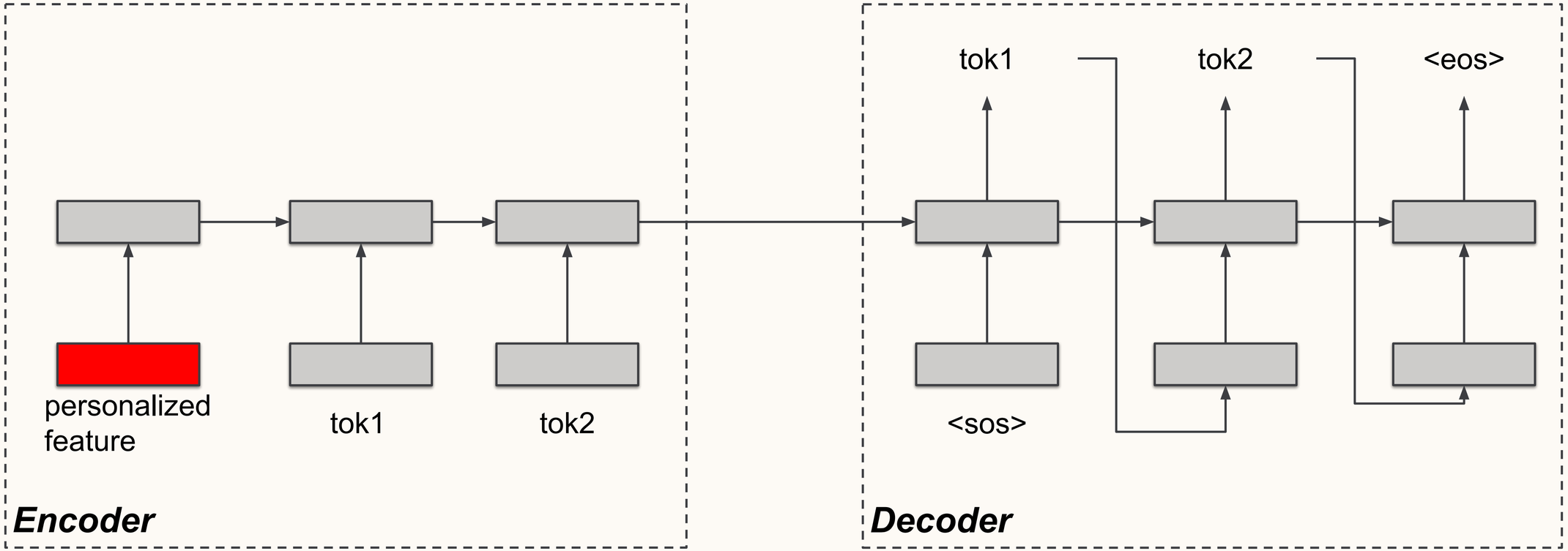
Sequence-to-sequence Framework



Sequence Generation - Deep Learning

(Zhong et al. 2020)

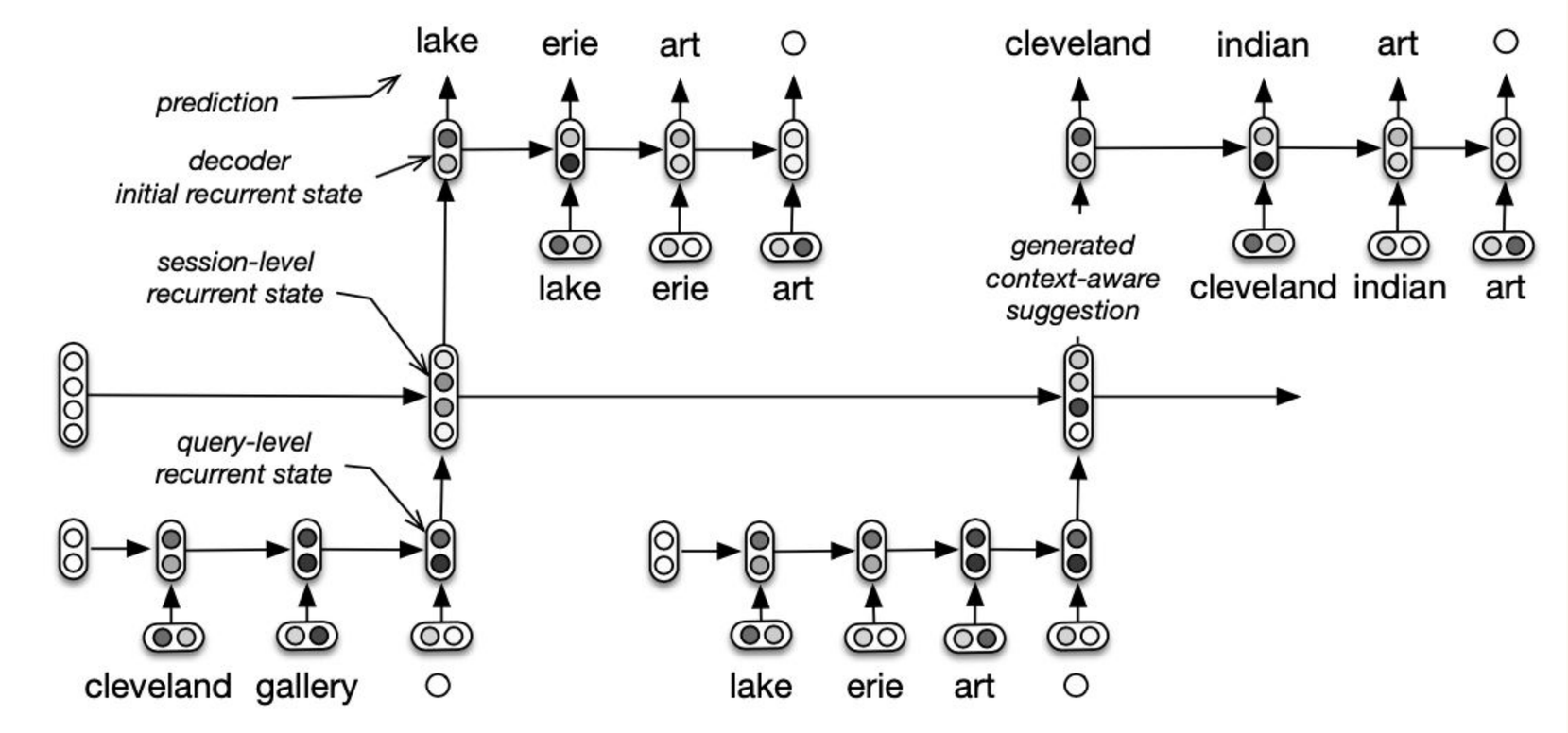
Incorporate Personalized Features



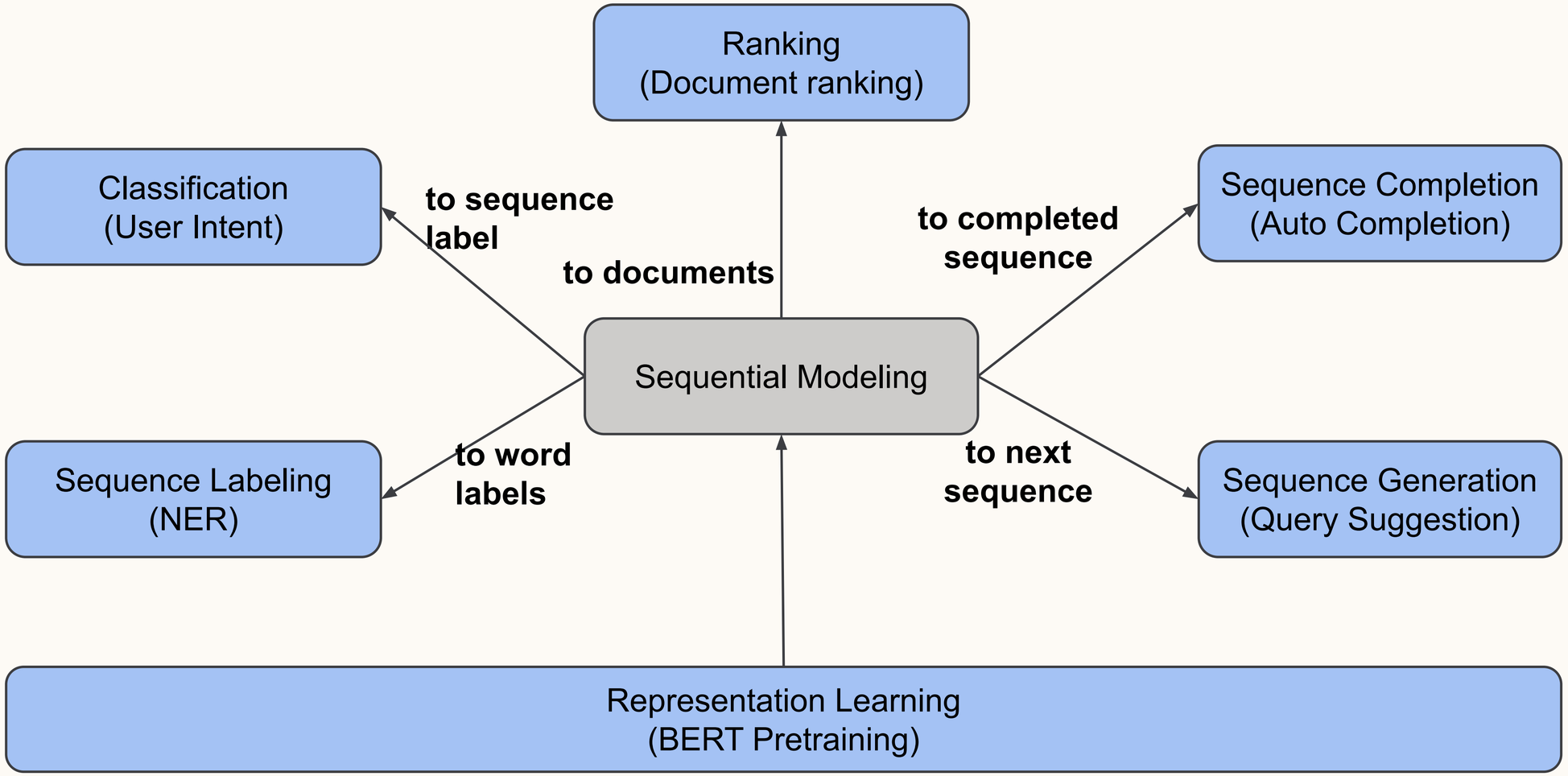
Sequence Generation - Deep Learning

(Sordoni et al. 2015, Kazi et al. 2020)

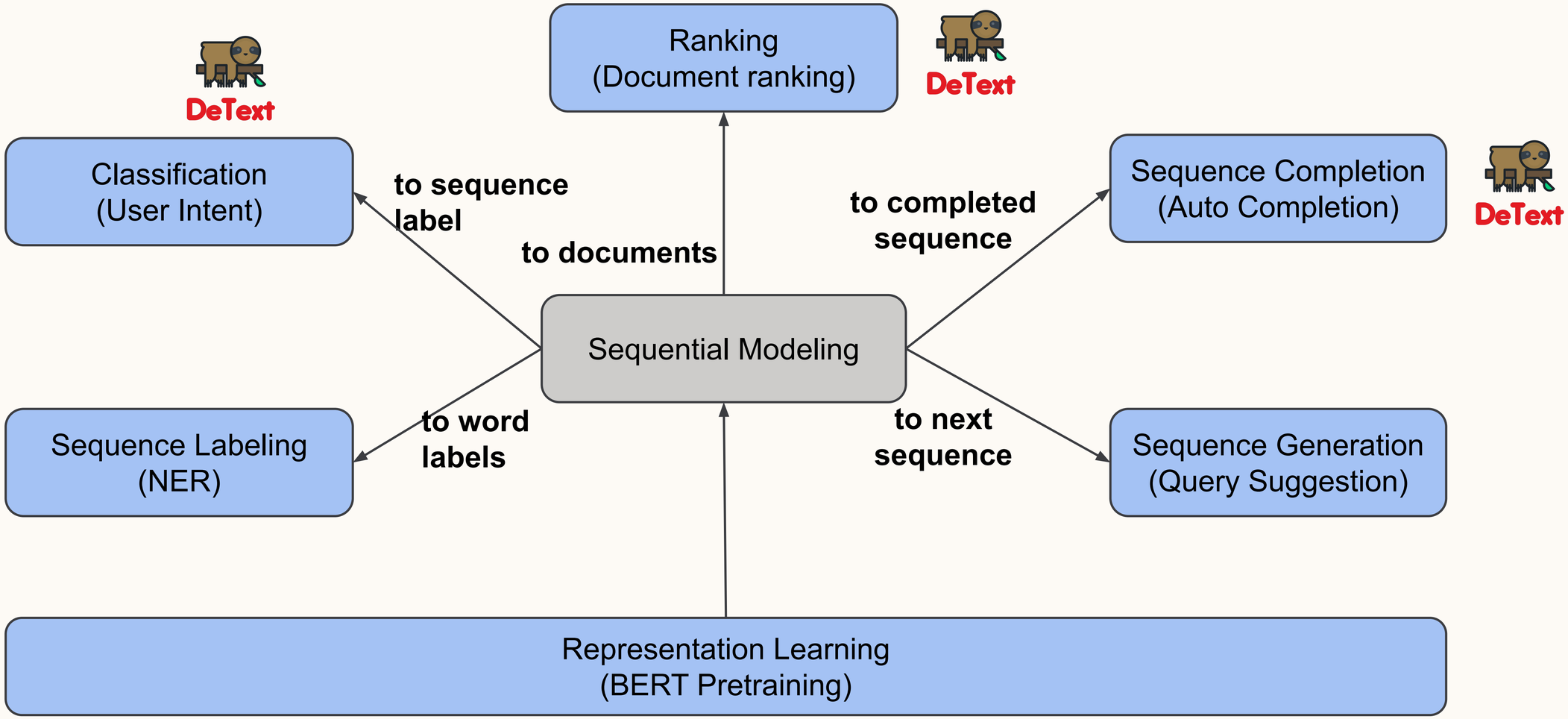
Incorporate Session Data



Query and User Understanding



DeText: a deep text understanding framework



DeText: a deep text understanding framework

- Github
  https://github.com/linkedin/detext
- LinkedIn Engineering Blog
- Publications:
  - DeText for Search Ranking
  - Query Intent
  - Query Auto-completion
  - Personalized Query Suggestion, Seq2seq with User Feedback

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LinkedIn

Query & User Understanding

Hands-on: Query Intent Classification & Query Auto Completion

Xiaowei Liu

Sida Wang

KDD 2020

LinkedIn

Deep Learning for Search and Recommender Systems in Practice

-

Candidate Retrieval

Huiji Gao

KDD 2020

Candidate Retrieval

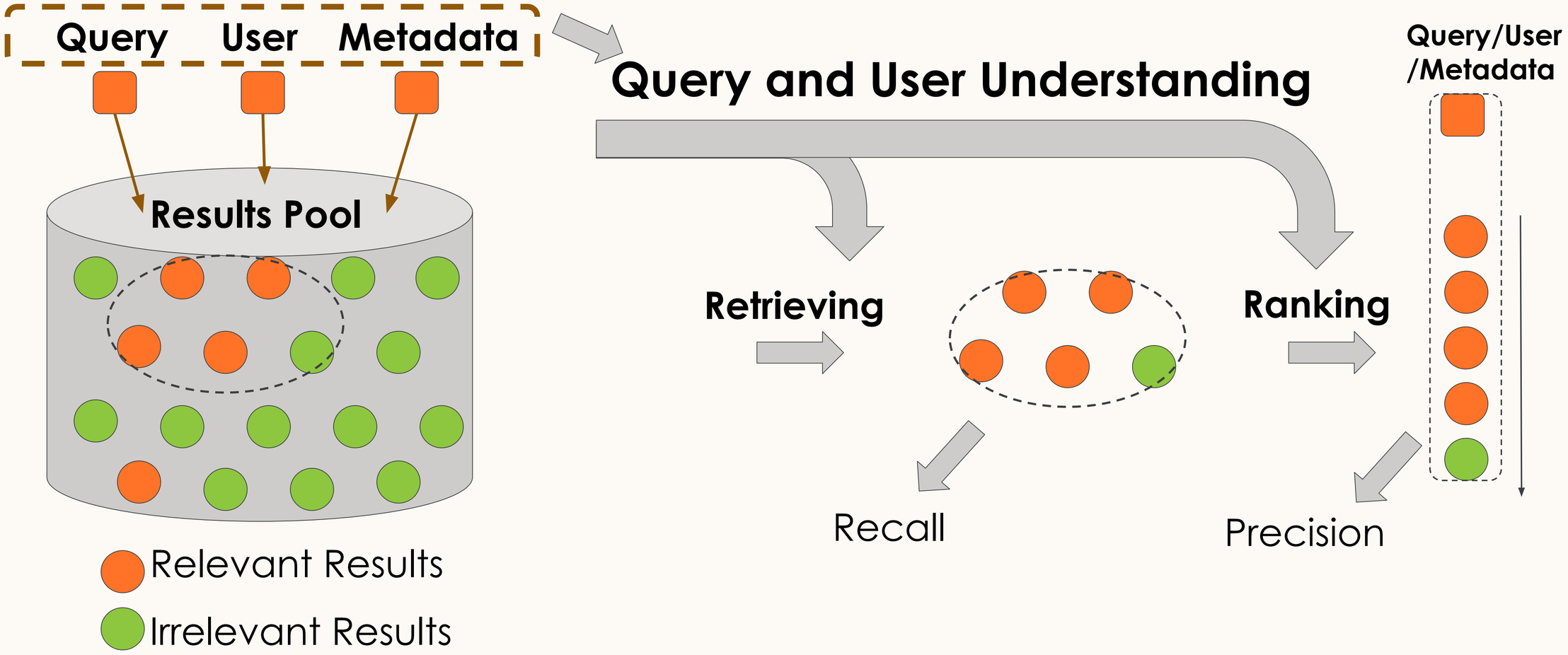
1 **Candidate Retrieval in General**

2 Lexical Based Retrieval

3 Embedding Based Retrieval

Candidate Retrieval

Retrieval 101



Candidate Retrieval

General "Query" in Search and Recommender Systems

- **Search Query**
  Input by a user in search systems, e.g., "KDD 2020"

- **User Profile**
  Key phrase from User Profiles to represent "query" in Recommender Systems, e.g., "Machine Learning Engineer" in a user's job title

- **Metadata**
  Used as filters, such as the "location" filter in search or targeting properties in ads

Candidate Retrieval

1 Candidate Retrieval in General

2 **Lexical Based Retrieval**

3 Embedding Based Retrieval

Lexical-based Retrieval

- **Keyword Based Retrieval**

Query: Mike Apple Software Engineer

Inverted Index (Boolean)

mike	Doc_1, **Doc_2**, **Doc_4**, **Doc_5**, ...
apple	**Doc_2**, **Doc_4**, **Doc_5**, Doc_7, ...
software	**Doc_2**, **Doc_4**, **Doc_5**, Doc_11, ...
engineer	Doc_1, **Doc_2**, **Doc_4**, **Doc_5**, …
developer	Doc_2, Doc_10, Doc_11, Doc_20, ...

Return: **Doc_2, Doc_4, Doc_5**

Lexical-based Retrieval

- **Keyword Based Retrieval**

Query: Mike Apple Software Engineer

Inverted Index (Doc Weights)

mike	Doc_1:1.0, **Doc_2:1.0**, **Doc_4:3.0**, **Doc_5: 1.0**, ...
apple	**Doc_2:2.0**, **Doc_4:3.0**, **Doc_5:1.0**, Doc_7: 2.0, ...
software	**Doc_2:1.0**, **Doc_4:1.0**, **Doc_5:2.0**, Doc_11: 1.0, ...
engineer	Doc_1:2.0, **Doc_2:1.0**, **Doc_4:2.0**, **Doc_5: 3.0**, …
developer	Doc_2:1.0, Doc_10:3.0, Doc_11:2.0, Doc_20: 1.0, ...

Return: **Doc_4**:9.0 > **Doc_5**:7.0 > **Doc_2**:5.0

Lexical-based Retrieval

- **Entity Based Retrieval**
  - **Understanding Queries with Entity Tagging**

Query: Mike Apple Software Engineer

Mike Apple Software Engineer
FN CN T T

Inverted Index (Boolean)

FN:{mike}	Doc_1, **Doc_2**, **Doc_4**, Doc_5, ...
CN:{apple}	**Doc_2**, **Doc_4**, Doc_6, Doc_7, ...
T:{software}	**Doc_2**, **Doc_4**, Doc_5, Doc_11, ...
T:{engineer}	Doc_1, **Doc_2**, **Doc_4**, Doc_5, ...
T:{developer}	Doc_2, Doc_10, Doc_11, ...
U: {apple}	Doc_5, Doc_10, Doc_12, ...

Return: **Doc_2, Doc_4**

Lexical-based Retrieval

- **Keyword + Entity Based Hybrid Retrieval**

Query: Mike Apple Software Engineer KDD

Mike Apple Software Engineer KDD
FN CN T T

Inverted Index (Boolean)

FN:{mike}	Doc_1, **Doc_2**, **Doc_4**, Doc_5, ...
CN:{apple}	**Doc_2**, **Doc_4**, Doc_6, Doc_7, ...
T:{software}	**Doc_2**, **Doc_4**, Doc_5, Doc_11, ...
T:{engineer}	Doc_1, **Doc_2**, **Doc_4**, Doc_5, …
T:{developer}	Doc_2, Doc_10, Doc_11, ...
KDD	Doc_1, **Doc_2**, Doc_3, ...

Return: **Doc_2**

Challenges on Lexical Matching Based Retrieval

- **Semantic Matching**
  "Software Engineer" v.s. "Software Developer"

- **Language Variants**
  "Baby" v.s. "Babies", "Tooth" v.s. "Teeth"

- **Spelling Errors**
  "*Infarmation* Retrieval"

Candidate Retrieval

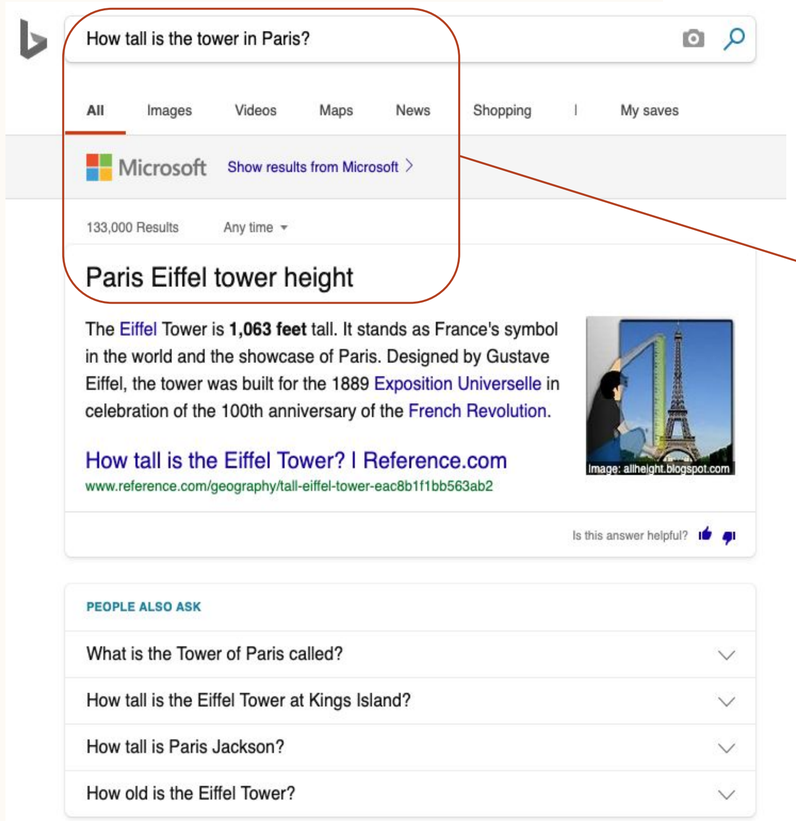
1 Candidate Retrieval in General

2 Lexical Based Retrieval

3 **Embedding Based Retrieval**

Embedding Based Retrieval

- **Retrieval based on Query/Document Embeddings: A Toy Example**



Why Embedding Based Retrieval?

Eiffel tower is **implicit** in the search query

"People also ask" provides **similar** queries / questions

✅ "Tower in Paris" - "Eiffel tower"
✅ "How tall" - "Height"

Embedding Based Retrieval

Embedding Based Retrieval

- **Why Embedding Based Retrieval**

Retrieval based on Query/Document Embeddings

  - **Semantic Match**

  - **Language Variants**

  - **Spelling Errors**

Embedding Based Retrieval

- **What is Embedding Based Retrieval**

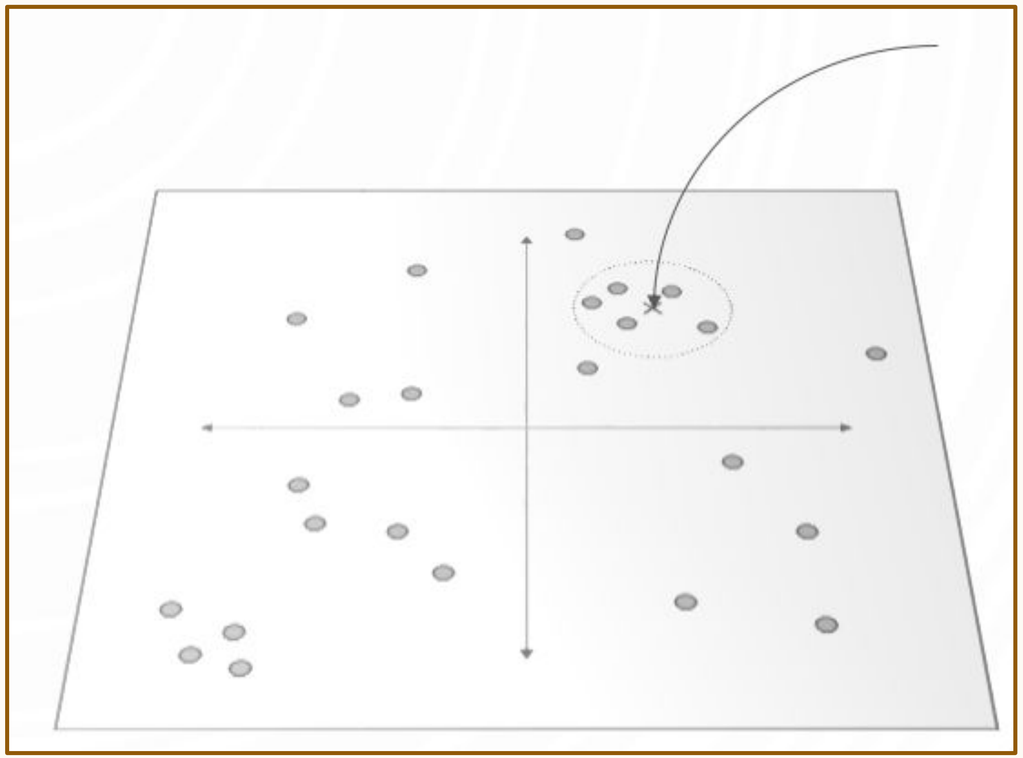
Definition:

The task to find closest points in a set to a given point.

Retrieval task: find the most relevant documents from the corpus to a query in the embedding space.

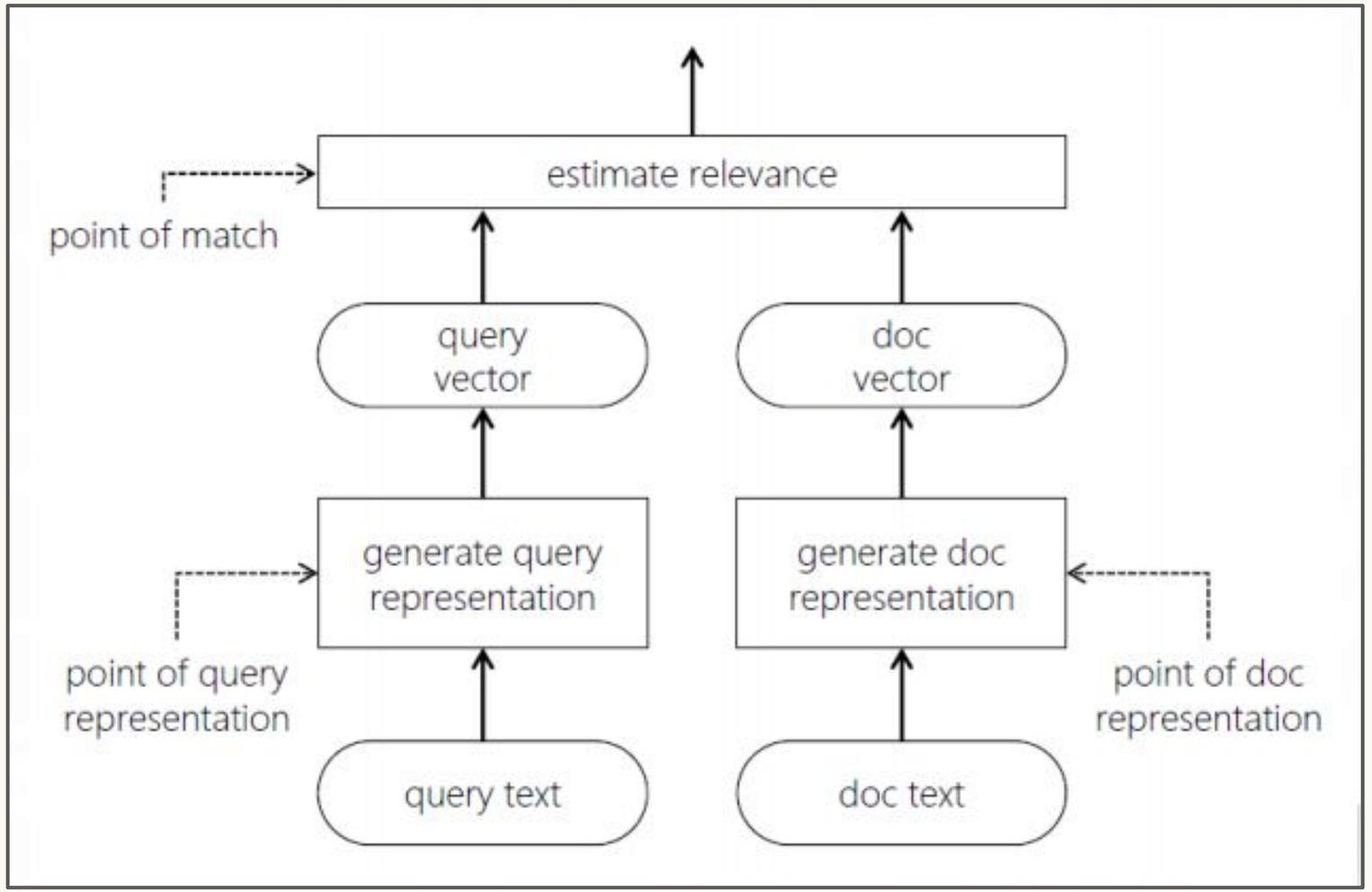
Retrieval for the concept rather than the keywords: Q&A, image, video etc.

Synonyms: vector search, semantic search, inexact search, KNN search



Embedding Based Retrieval

- **Overview**



Embedding Based Retrieval

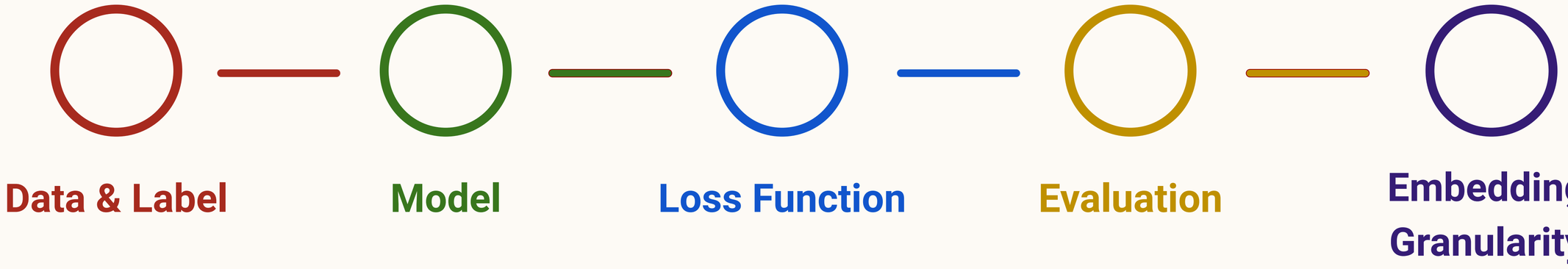
- **How to**

Embedding Generation	Generate query and document embeddings under the same feature space
Index Building	Index embeddings while optimizing on effectiveness and efficiency
KNN Retrieval	Retrieval top K documents based on the query embedding and index

Embedding Based Retrieval

Embedding Generation

- **Ensure Query and Document Embeddings are under the Same Feature Space**



Embedding Based Retrieval

Embedding Generation - Data & Label

- **(Query, Doc) Pairs**
- **Labels: Positive / Negative / Hard Negative / Hard Positive**
  - Positive: Impressed and Clicked
  - Negative: Not-impressed and Not Relevant
  - Hard Negative: Impressed and Not-Clicked
  - Hard Positive: Not-impressed and Relevant

Embedding Based Retrieval

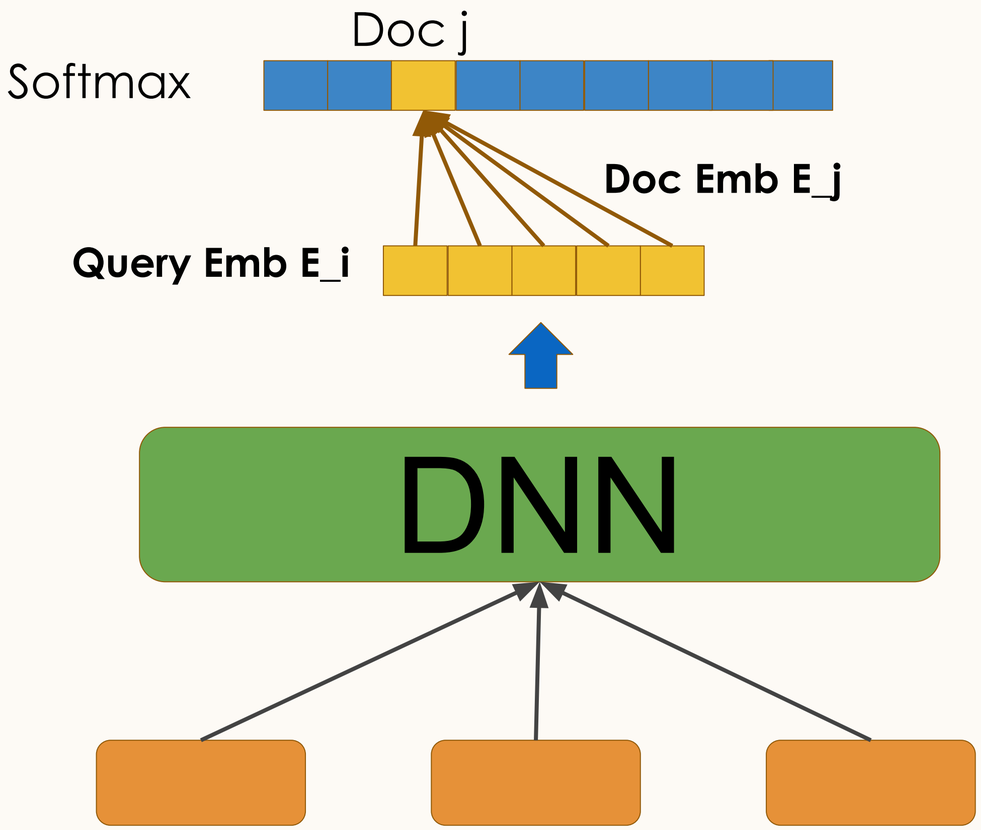
Embedding Generation - Model & Loss Function

- **Neural Networks for Embedding Generation**
  - Model the Relevant ***Doc*** Based on the ***Query*** input
  - Model Relevance Score Based on the Input from <***Query***, ***Doc***>
- "***Query***" refers to the general concept which can be User Profiles, Historical Activities, Search Queries, etc

Embedding Based Retrieval

Embedding Generation - Model & Loss Function

- **Neural Networks for Embedding Generation**



Query Input (Profiles, Historical Activities, Search Queries, etc)

Model the Relevant ***Doc*** based on a ***Query***

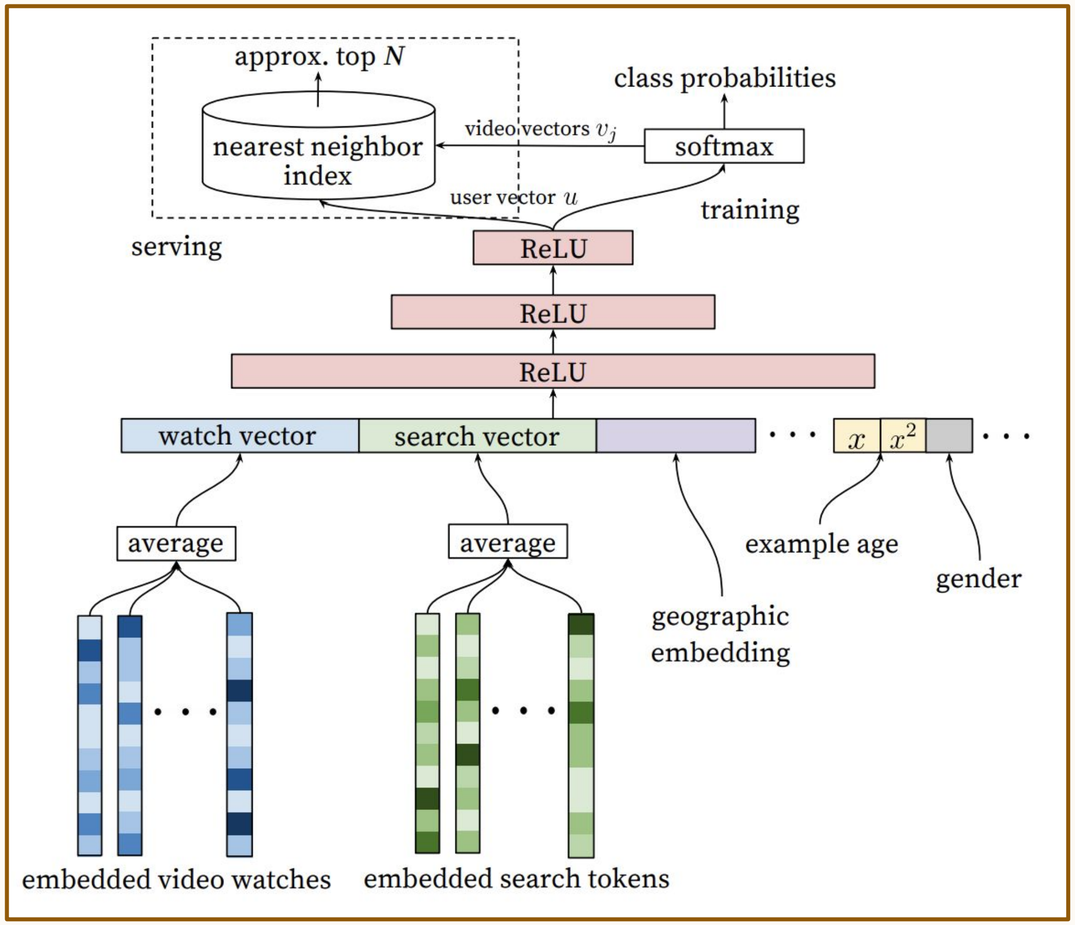
- Input: Query/User-level Data
- Target: Doc id to be clicked (or other actions) by the user given the current user status
- Generated Embeddings:
  - Query/User Embeddings & Doc Embeddings
- Loss Function:
  - Softmax on the targeted doc id

Embedding Based Retrieval

[Paul etal 2016]

Embedding Generation - Model & Loss Function

- **Neural Networks for Embedding Generation**



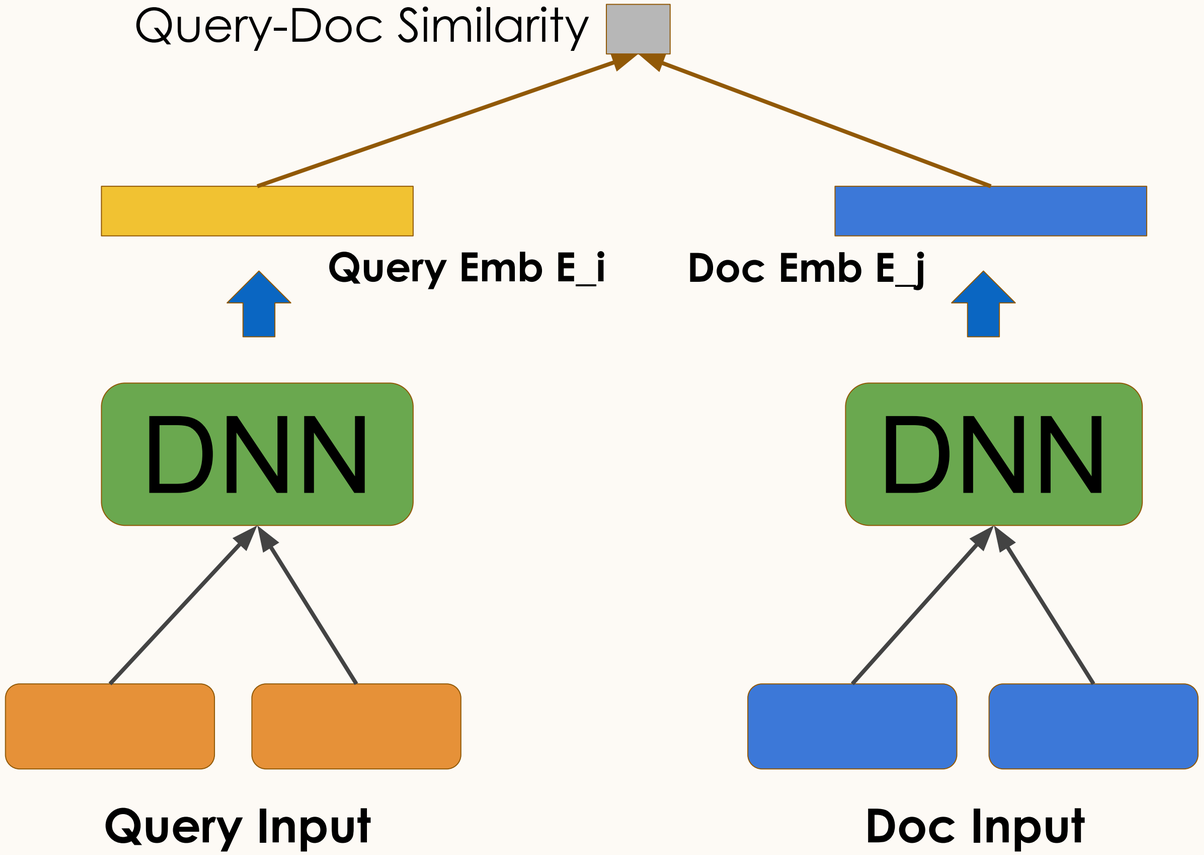
Model the Relevant ***Doc*** based on a ***Query***

- Input: Query/User-level Data
- Target: Doc id to be clicked (or other actions) by the user given the current user status
- Generated Embeddings:
  - Query/User Embeddings & Doc Embeddings
- Loss Function:
  - Softmax on the targeted doc id

Embedding Based Retrieval

Embedding Generation - Model & Loss Function

- **Neural Networks for Embedding Generation**



Model Relevance Score based on the input <***Query***, ***Doc***>

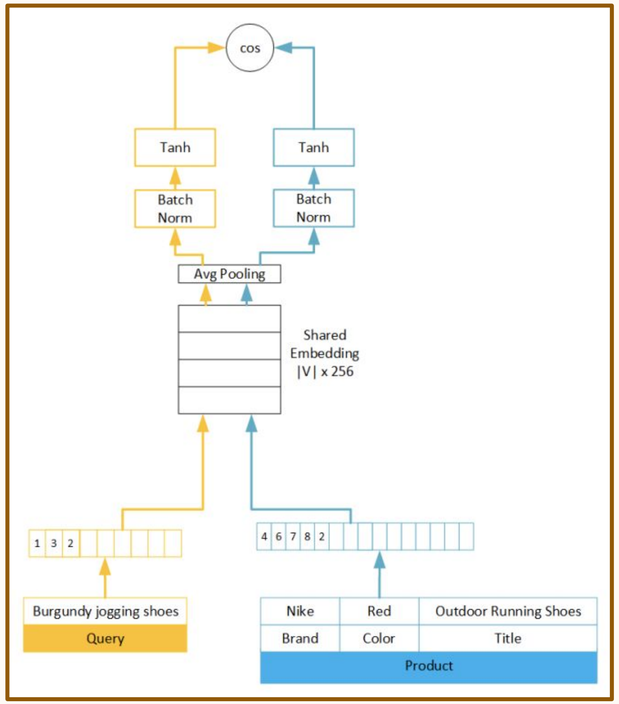
- Input: Query/User-level & Doc-level Data
- Target: Relevance Score of the <Query, Doc>
- Generated Embeddings:
  - Query/User Embeddings & Doc Embeddings
- Loss Function:
  - Loss: 2-part / 3-part Hinge Loss

Embedding Based Retrieval

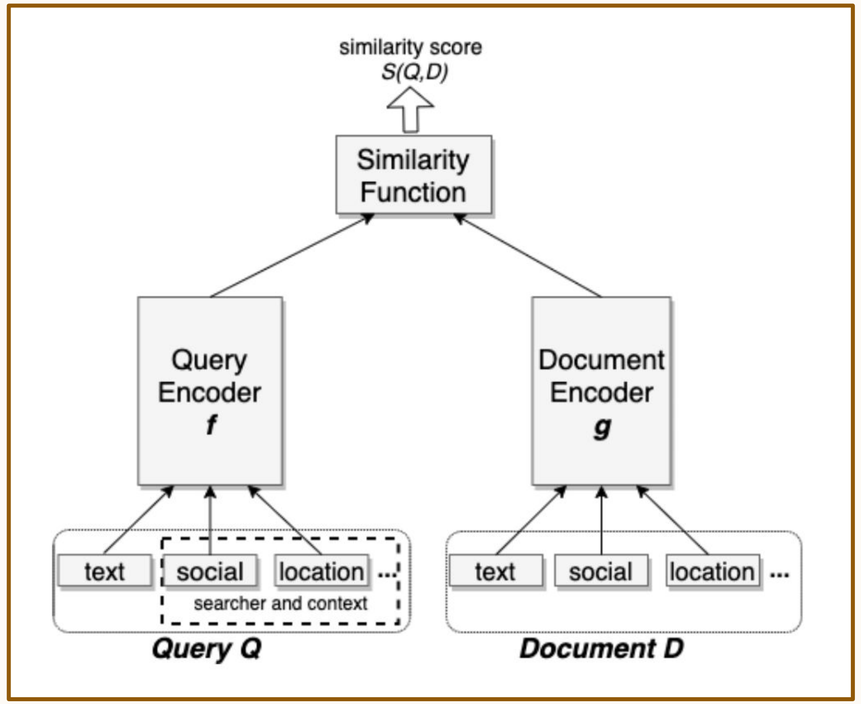
[Priyanka etal 2019; Jui-Ting etal 2020; Han etal 2020]

Embedding Generation - Model & Loss Function

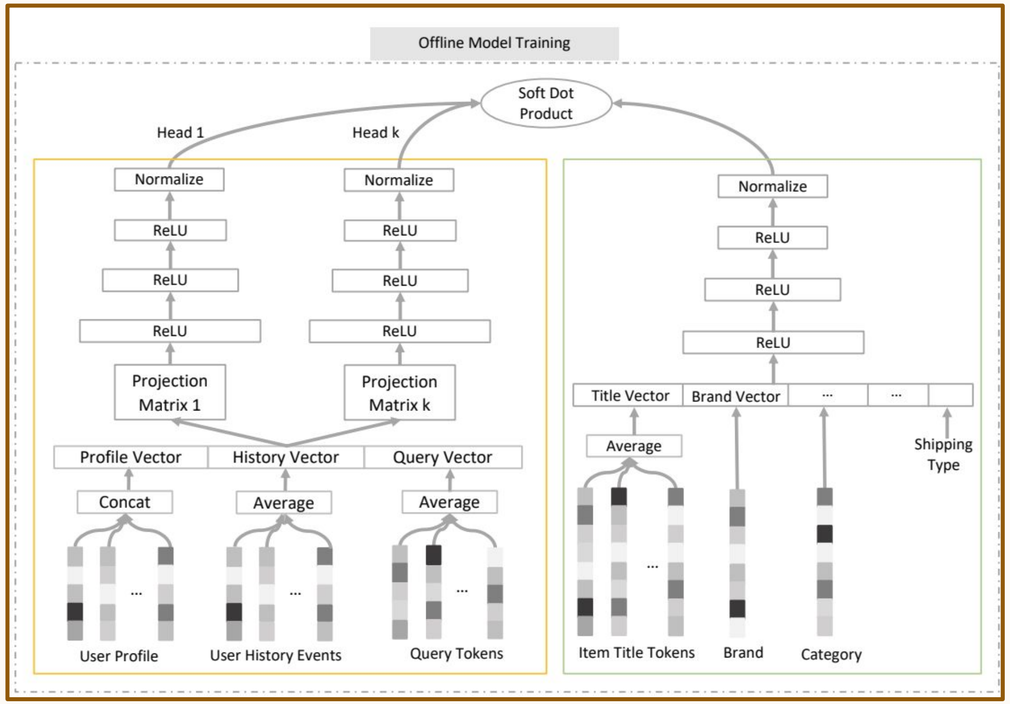
- **Neural Networks for Embedding Generation**



[Priyanka etal 2019]



[Jui-Ting etal 2020]



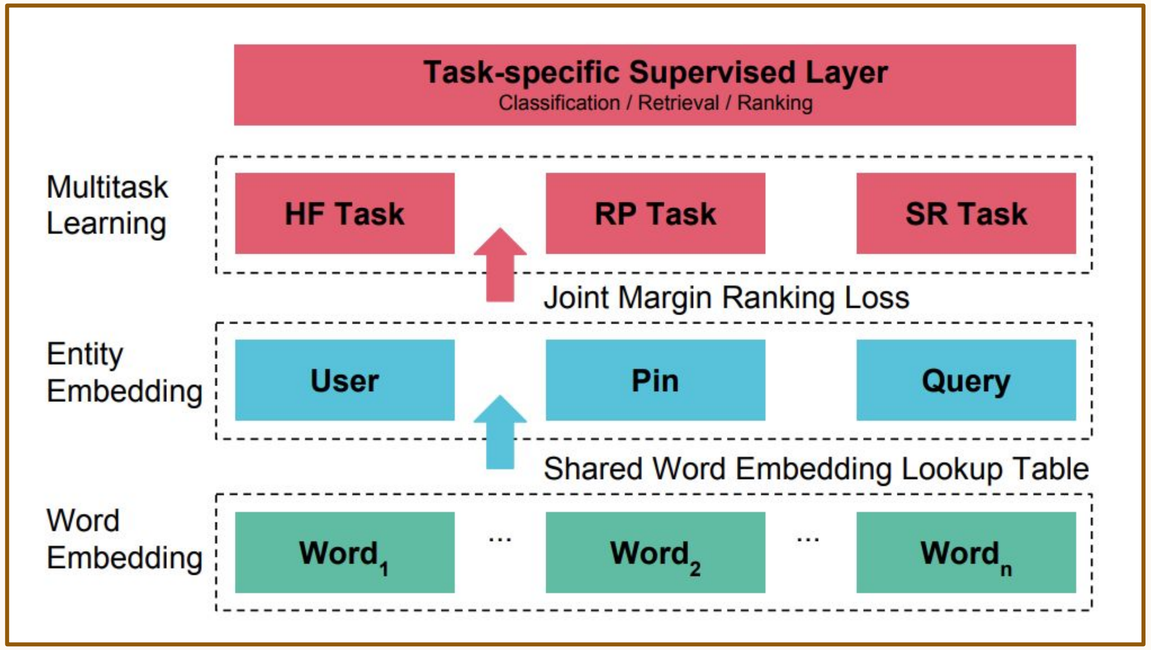
[Han etal 2020]

Embedding Based Retrieval

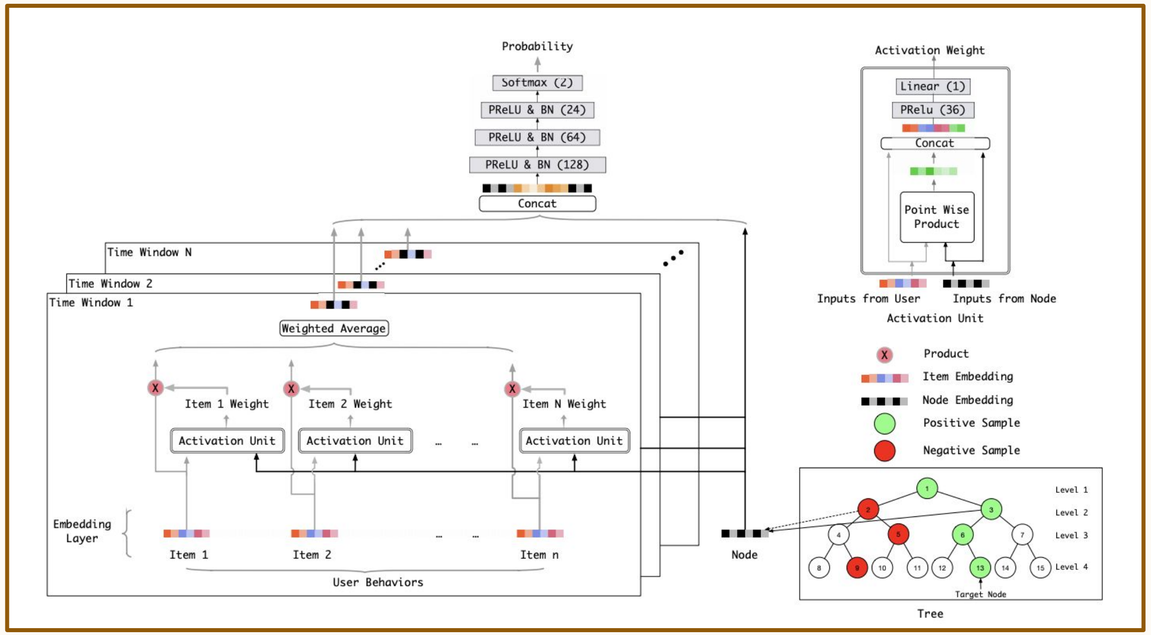
[Han etal 2018; Jinfeng etal 2019]

Embedding Generation - Model & Loss Function

- **Neural Networks for Embedding Generation**



[Han etal 2018]



[Jinfeng etal 2019]

Embedding Based Retrieval

[Jui-Ting etal 2020]

Embedding Generation - Evaluation Metrics & Embedding Granularity

- Evaluate Recall@K

$$\text{recall@K} = \frac{\sum_{i=1}^{K} d_i \in T}{N}$$

d_i : the i-th document from top K retrieved docs
T: the target Result Set {t_1, t_2, …, t_N}

- Embedding Granularity
  - Word level
  - Entity level
  - Sentence level
  - Document level

Embedding Based Retrieval

Index Building

- **Compatible with Inverted Index Systems**
  - Product Quantization
  - Locality-Sensitive Hashing (LSH)

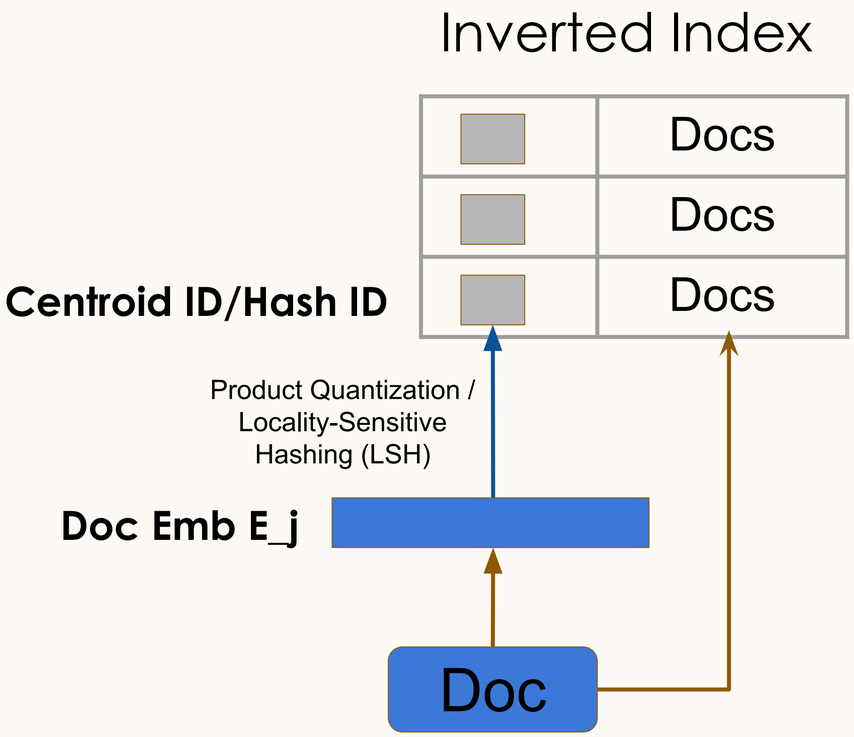
- **Non-compatible with Inverted Index Systems**
  - Hierarchical Navigable Small World (HNSW)

Embedding Based Retrieval

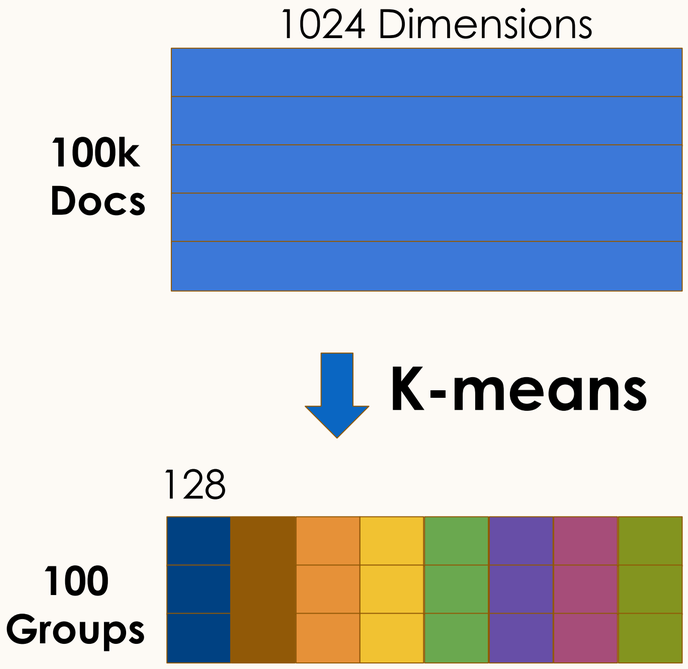
[Herve etal 2010; Chris etal 2017]

Index Building

- **Compatible with Inverted Index Systems**



- Product Quantization



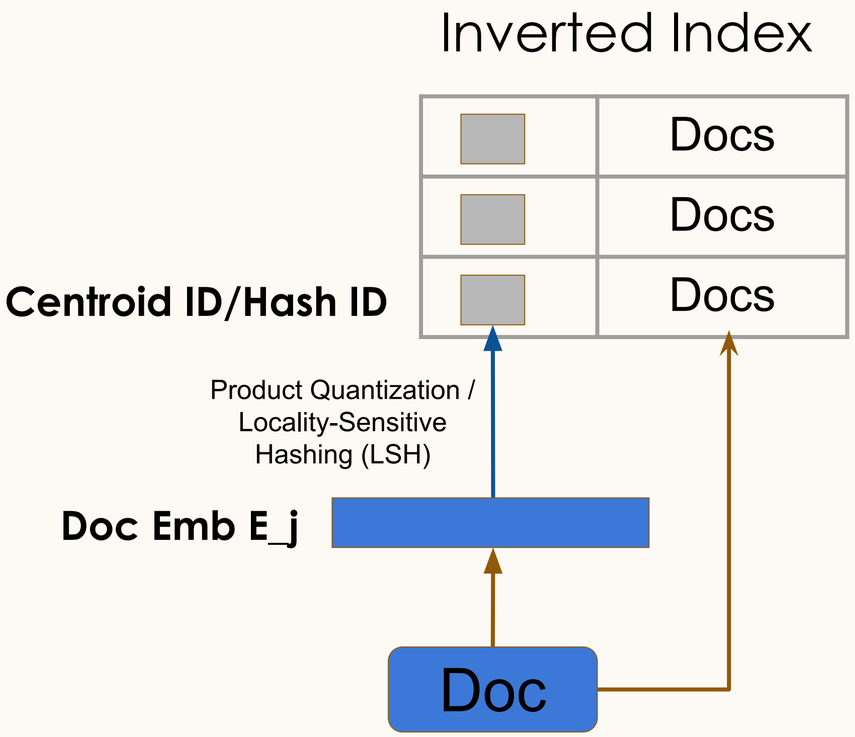
- 100 x 8 centroids, each centroid is represented by a 128 dimension vector
- Each embedding can be represented by 8 centroid embedding vectors, based on its distance to each centroid
- The centroids can be used as keys in inverted index

- Locality-Sensitive Hashing (LSH)

Embedding Based Retrieval

Index Building

- **Compatible with Inverted Index Systems**

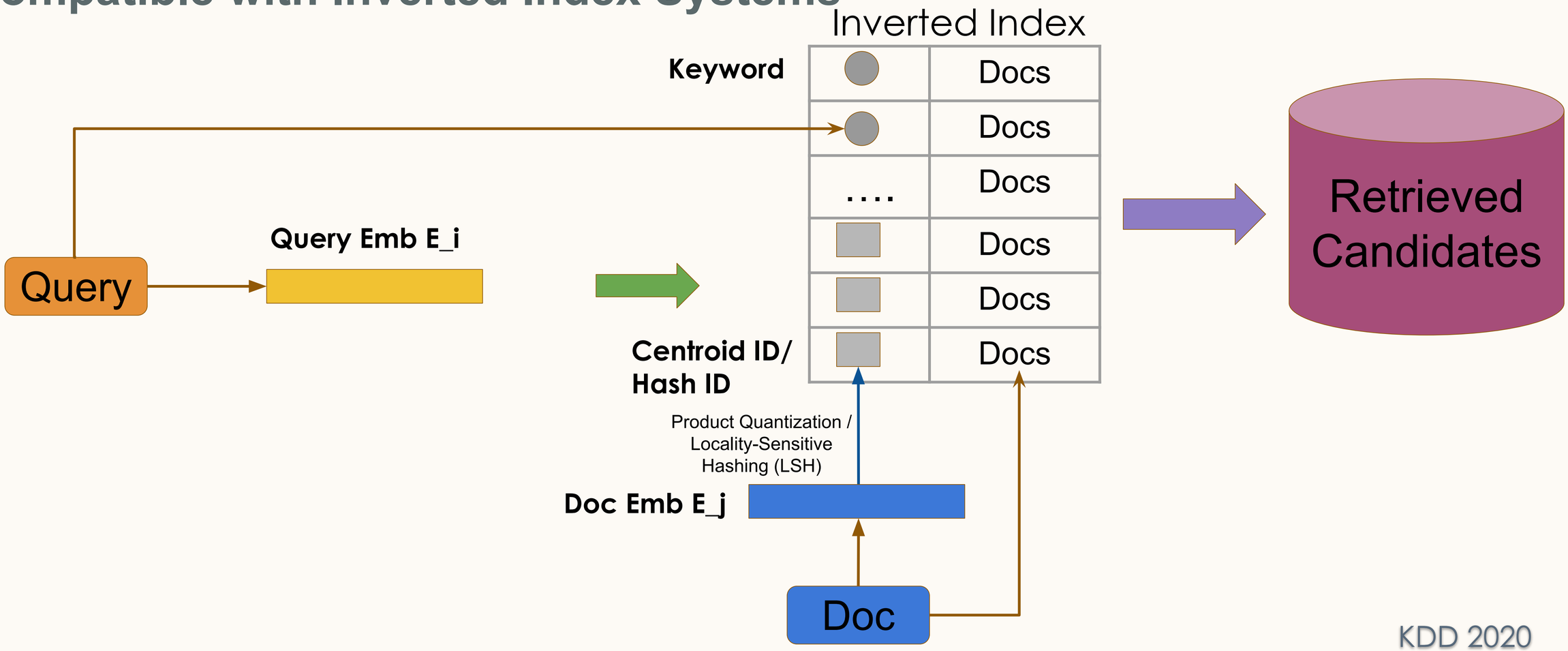


- Product Quantization
- Locality-Sensitive Hashing (LSH)
  - Hash functions are specifically designed so that hash value collisions are *more likely* for two input values that are *close together* than for inputs that are *far apart*. Therefore, similar docs have a high probability to map to the same hash id.

Embedding Based Retrieval

KNN Retrieval

- **Compatible with Inverted Index Systems**

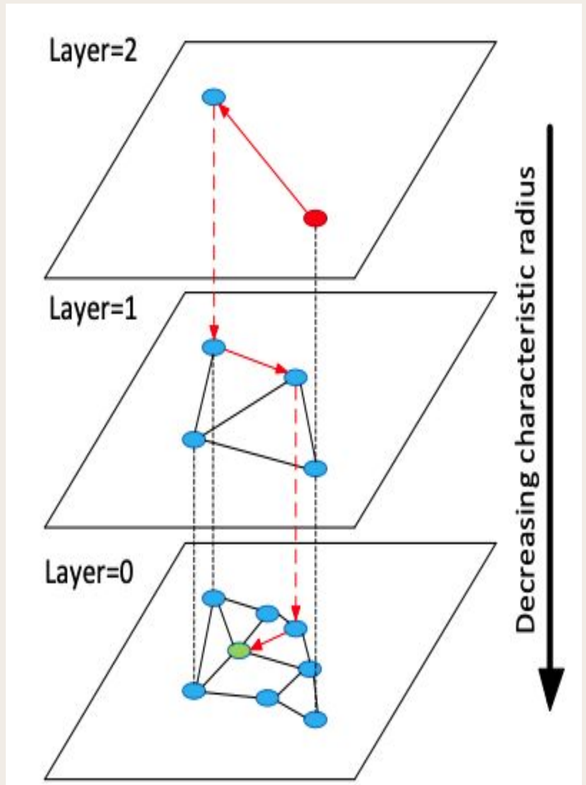


Embedding Based Retrieval

(Yu etal 2016; Qi etal 2018)

Index Building

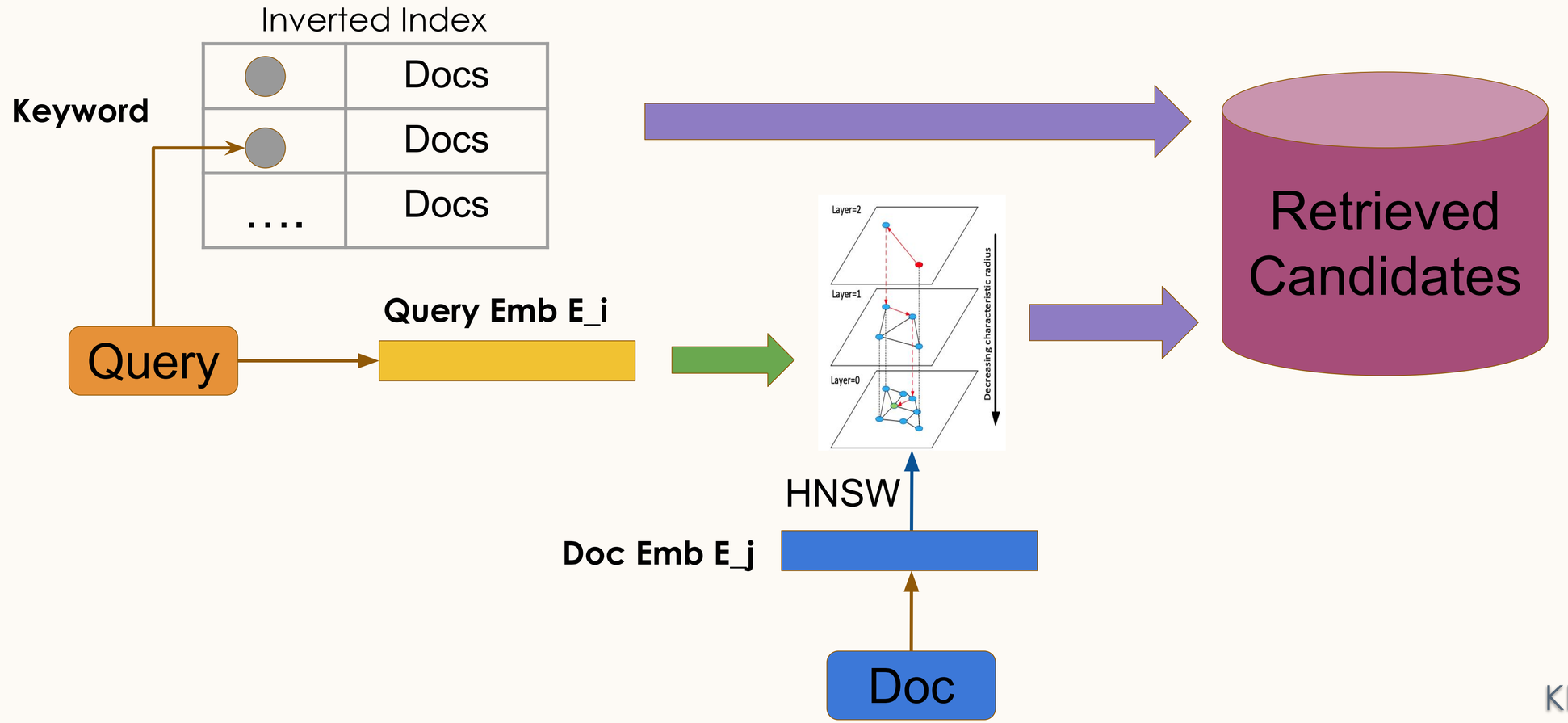
- **Non-compatible with Inverted Index Systems**
  - Hierarchical Navigable Small World (HNSW)



Embedding Based Retrieval

KNN Retrieval

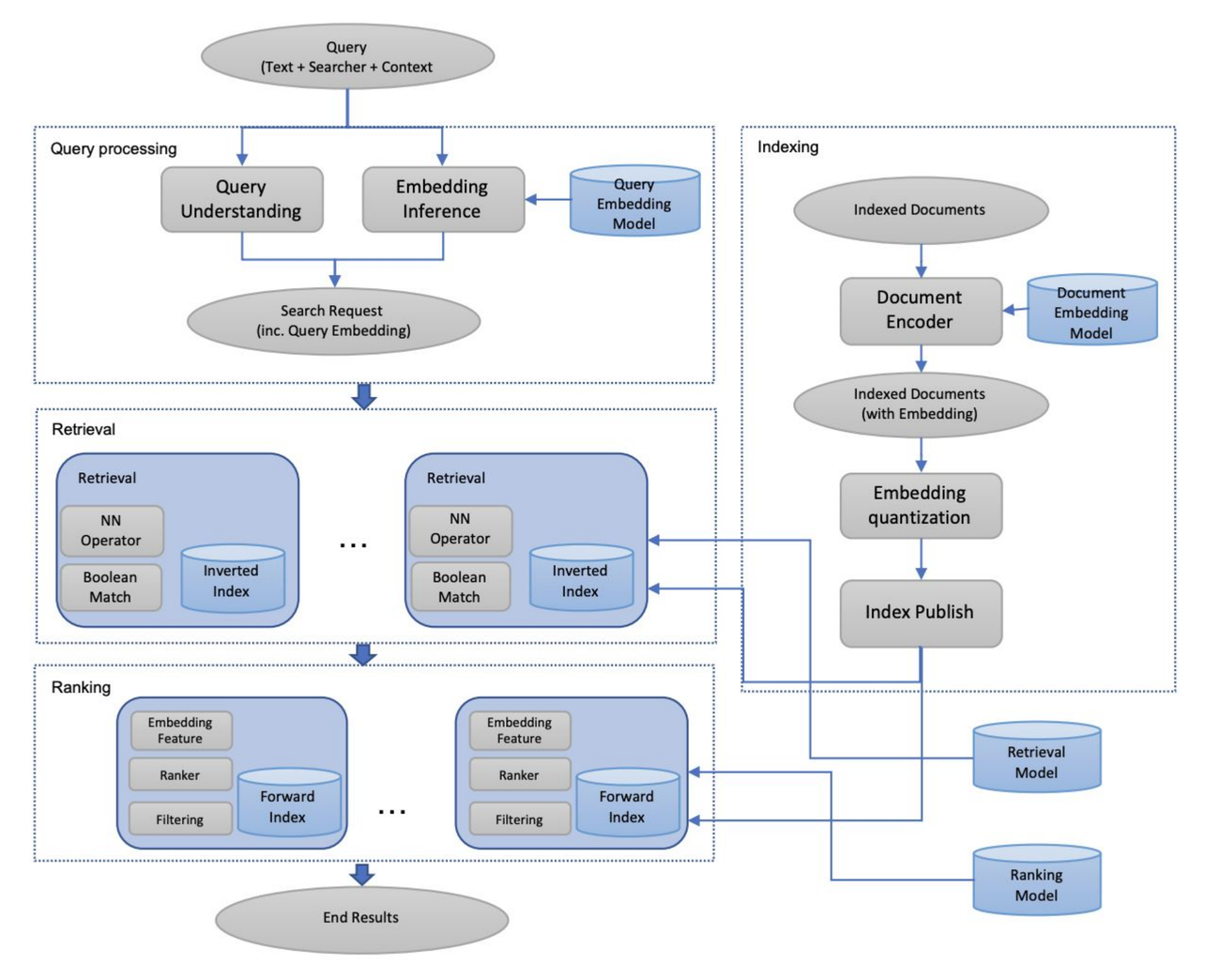
- **Non-compatible with Inverted Index Systems**
  - Hierarchical Navigable Small World (HNSW)



Embedding Based Retrieval

[Jui-Ting etal 2020)

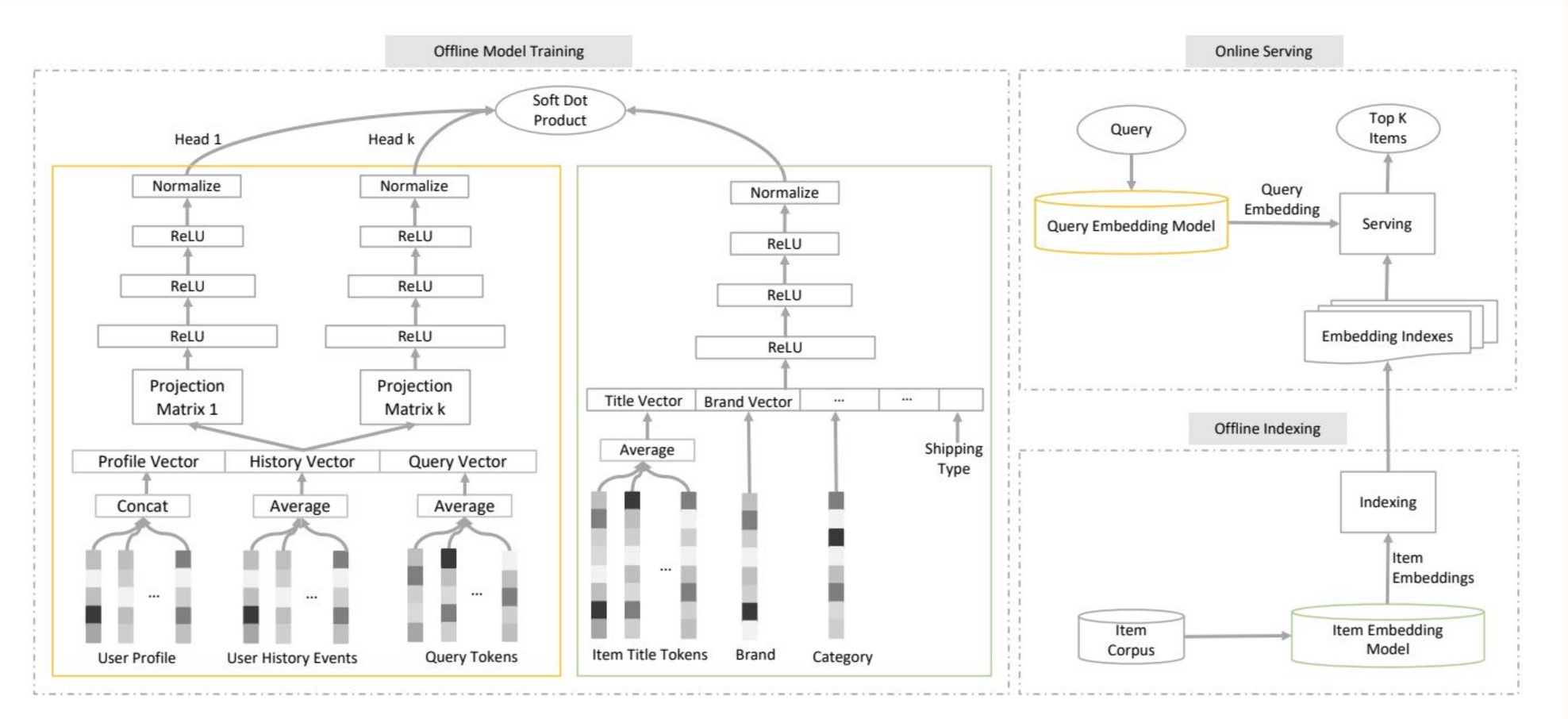
The end-to-end System



Embedding Based Retrieval

[Han etal 2020)

The end-to-end System



Candidate Retrieval

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Candidate Retrieval

Hands-on: Deep Learning Retrieval

Zhoutong Fu

KDD 2020

LinkedIn

Deep Learning for Search and Recommender Systems in Practice

-

Learning to Rank

Jun Shi

KDD 2020

Learning to Rank

1 **System Overview**

2 Metrics for Evaluation

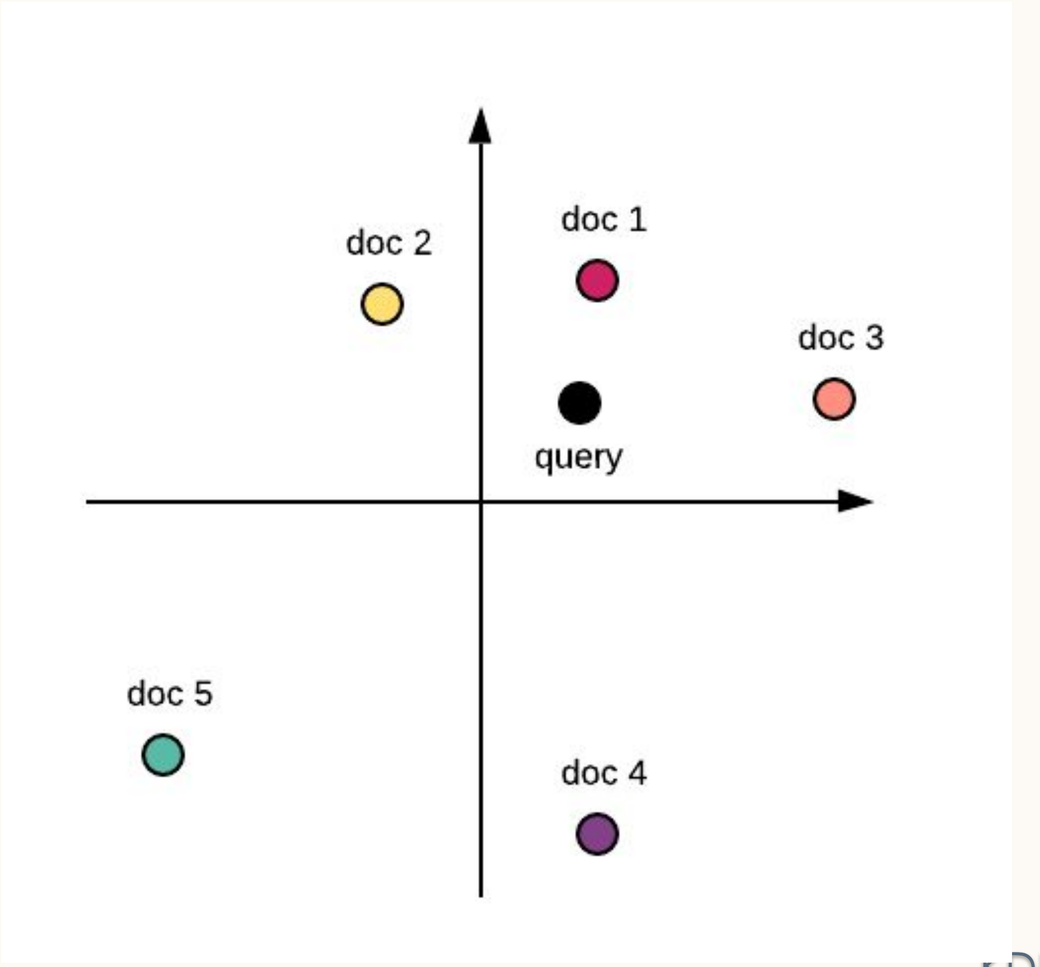
3 Ranking Models

System Overview

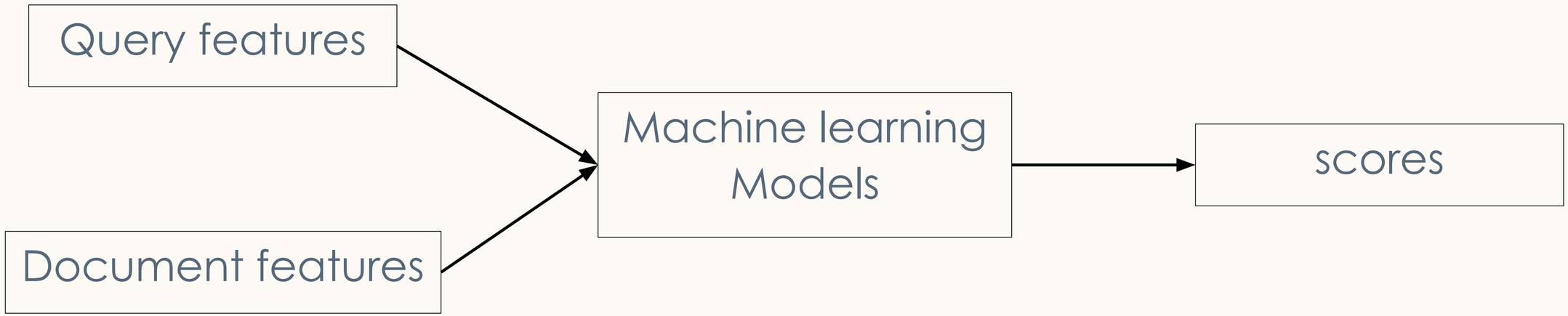
- Document Retrieval
- Scoring and Ranking
- Personalization and Re-ranking

Document Retrieval

- Simple regex based retrieval
- Traditional inverted index based retrieval
- Embedding based retrieval



Scoring and Ranking



Learning to Rank

1 System Overview

2 **Metrics for Evaluation**

3 Ranking Models

Metrics for Evaluation

- Multiple level of relevance
  - NDCG (Normalized Discounted Cumulative Gain)
- Binary relevance
  - MAP (Mean Average Precision)
  - MRR (Mean Reciprocal Rank)

Normalized Discounted Cumulative Gain

Discounted Cumulative Gain

$$\mathrm{DCG_p} = \sum_{i=1}^{p} \frac{rel_i}{\log_2(i+1)} = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i+1)}$$

Normalized Discounted Cumulative Gain

$$\mathrm{nDCG_p} = \frac{DCG_p}{IDCG_p},$$

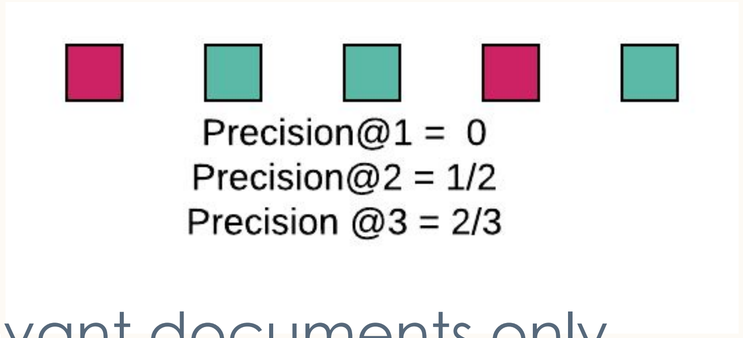
where

$$\mathrm{IDCG_p} = \sum_{i=1}^{|REL_p|} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

https://en.wikipedia.org/wiki/Discounted_cumulative_gain

Mean Average Precision

Precision@K: Relevant documents up to rank K / K



Average Precision: Average over K for relevant documents only

Precision@2 = ½, Precision@3 = ⅔, Precision@5 = ⅗
Average Precision = (½ + ⅔ + ⅗)/3 = 0.59

Mean Average Precision: Average precision across all queries.

Mean Reciprocal Rank

Reciprocal Rank

$$\frac{1}{\text{rank}_i}$$

Mean Reciprocal Rank

$$\text{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{\text{rank}_i}.$$

Learning to Rank

1 System Overview

2 Metrics for Evaluation

3 **Ranking Models**

Ranking Models

- Vector space models
  - Latent semantic indexing (co-occurrence vector -> latent semantic space vector)
- Probabilistic models
  - BM25 (bag-of-word, TF-IDF based scoring function)
  - Statistical language model (Probability of the query given a document)
- Learning to rank models
  - Ordinal regression
  - Ranking SVM
  - LambdaRank

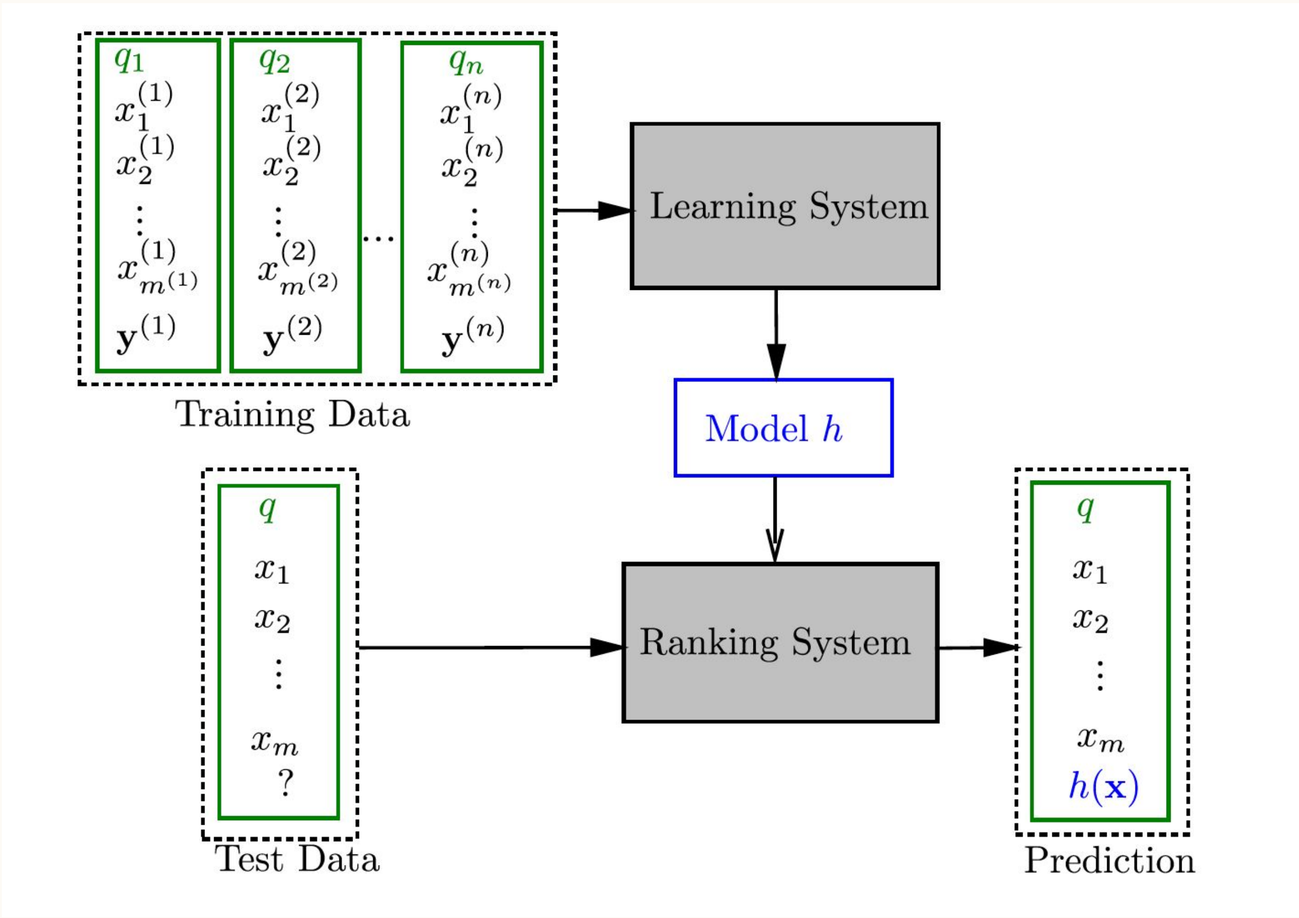
Learning to Rank

- Pointwise ranking
- Pairwise ranking
- Listwise ranking

Ranking model

key components:

- Input
- Label
- Loss function



T.-Y. Liu, Learning to Rank for Information Retrieval Foundations and Trends in Information Retrieval, Vol. 3, No. 3 (2009) 225-331

Pointwise Ranking

Loss function is based on a single (query, document) pair.

- Regression based Algorithms
- Classification based Algorithms
- Ordinal Regression based Algorithms

Regression based pointwise ranking

Input (q, x) feature vector responding to the query and a document.

Label: y, relevance of the document.

Loss function: $L(q, x, y) = |f(q,x) - y|^2$

Scoring function tries to approximate the labels by minimizing the mean squared error

Classification based pointwise ranking

Input (q, x) feature vector responding to the query and a document.

Label: y, relevance of the document.

Loss function: cross entropy loss between label and predicted probability.

Logistic regression example (binary relevance labels):

$$P(R|x_j) = \frac{1}{1 + e^{-c - \sum_{t=1}^{T} w_t x_{j,t}}}.$$

T.-Y. Liu, Learning to Rank for Information Retrieval Foundations and Trends in Information Retrieval, Vol. 3, No. 3 (2009) 225-331

Ordinal regression based pointwise ranking

Input (q, x) feature vector responding to the query and a document.

Label: y, relevance of the document.

Loss function: negative log likelihood.

Ordinal regression outputs the weights and the thresholds.

$$\Pr(y < i|q, x) = \text{sigmoid}(\theta_i - \mathbf{w}^T[\mathbf{q}, \mathbf{x}] + c),$$
$$\text{where } \theta_i \text{ is the } i\text{th threshold}$$

Crammer, K., Singer, Y.: Pranking with ranking. In: Advances in Neural Information Processing Systems 14 (NIPS 2001), pp. 641–647 (2002)

Summary of pointwise ranking

Pros

- Simple, considering one document at a time.
- Available algorithms are rich. Most regression/classification algorithms can be used.

Cons

- Pointwise ranking ignores other documents in the list that will affect the ranking result.
- Pointwise ranking does not achieve the correct objective. Ranking is about relative position, not absolute scores of individual documents.

Pairwise Ranking

Loss function is based on query and a pair of documents.

- RankNet
- Ranking SVM
- LambdaRank

Commonality of pairwise ranking algorithms

- Input: query **q** and a pair of documents $\mathbf{d}_i$ and $\mathbf{d}_j$,
  Label: $\mathbf{d}_i$ ranks before or after $\mathbf{d}_j$. Binary {-1, + 1} if we ignore ties.
- Scoring function: function of the query and the pair of documents, e.g. $f(\mathbf{q}, \mathbf{d}_i, \mathbf{d}_j)$ but in most cases, it is a function of query and one document, e.g. $f(\mathbf{q}, \mathbf{d}_i, \mathbf{d}_j) = s(\mathbf{q}, \mathbf{d}_i) - s(\mathbf{q}, \mathbf{d}_j)$

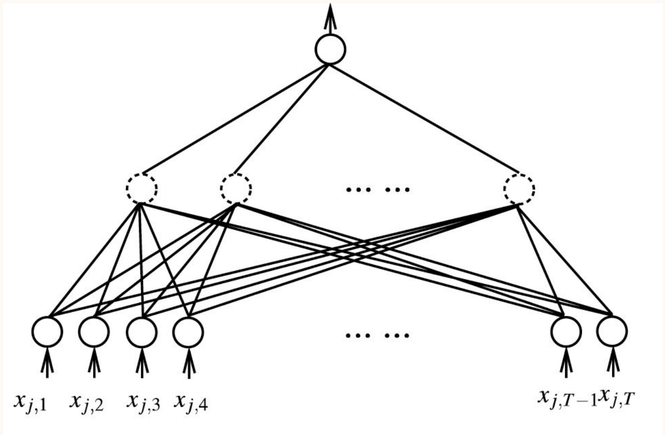
RankNet

- Input: query and a pair of documents ($\mathbf{q}$, $\mathbf{d_i}$, $\mathbf{d_j}$).
- Label: y_{ij} = +1 if $\mathbf{d_i}$ ranks higher than $\mathbf{d_j}$, -1 otherwise.
- Loss function: cross entropy loss function

$$L(\mathbf{q}, \mathbf{d_i}, \mathbf{d_j}) = -y_{ij} * \log P_{ij} - (1-y_{ij}) * \log(1-P_{ij})$$

where $P_{ij} = \text{sigmoid}(s(\mathbf{q}, \mathbf{d_i}) - s(\mathbf{q}, \mathbf{d_j}))$

- RankNet uses neural networks as the scoring function



- Burges, C.J., Shaked, T., Renshaw, E., Lazier, A., Deeds, M., Hamilton, N., Hullender, G., Learning to rank using gradient descent. Proceedings of the 22nd International Conference on Machine Learning (ICML 2005), pp. 89–96 (2005)
- T.-Y. Liu, Learning to Rank for Information Retrieval Foundations and Trends in Information Retrieval, Vol. 3, No. 3 (2009) 225-331

Ranking SVM

Apply SVM to a binary classification problem.

- +1 $\mathbf{d}_i$ ranks higher than $\mathbf{d}_j$
- -1 $\mathbf{d}_i$ ranks lower than $\mathbf{d}_j$

Linear scoring function s(**q**,**d**) = $\mathbf{w}^T\mathbf{x}$

$$\min \frac{1}{2}\|\mathbf{w}\|^2 + \sum_k \sum_{i,j:y_{i,j}^k=1} \xi_{i,j}^k$$

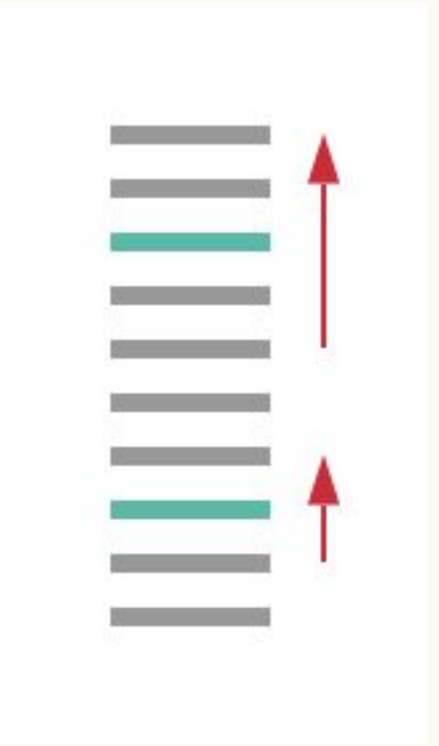
$$\text{s.t.} \quad \mathbf{w}^T(\mathbf{x}_i - \mathbf{x}_j) \geq 1 - \xi_{i,j}^k, y_{i,j}^k = 1$$

$$\xi_{i,j}^k \geq 0, k = 1, \ldots, n$$

Herbrich, R., Obermayer, K., Graepel, T., Large margin rank boundaries for ordinal regression. Advances in Large Margin Classifiers, pp. 115–132 (2000)

LambdaRank / LambdaMART

- The loss function is not explicit known, use evaluation metrics instead.
- Select a metric, e.g. NDCG. compute the NDCG for the current list.
- Select two documents, $\mathbf{d_i}$ and $\mathbf{d_j}$, assuming $\mathbf{d_i}$ is more relevant than $\mathbf{d_j}$.
- Swap $\mathbf{d_i}$ and $\mathbf{d_j}$'s positions in the list, compute Delta NDCG.
- Compute Lambda that is proportional to the Delta NDCG.
- Treat the Lambda as gradient and update the weights.
- LambdaMART uses gradient boosting trees models.



Burges, C.J., Ragno, R., Le, Q.V.: Learning to rank with nonsmooth cost functions. In: Advances, Neural Information Processing Systems 19 (NIPS 2006), pp. 395–402 (2007)

Summary of pairwise ranking

Pros:

- Considering relative relevance of pairs. Closer to the actual problem than pointwise ranking.
- Better relevance performance.

Cons:

- Complexity is higher than pointwise ranking.
- Only looking at pairs, not the entire list. Loss of information.

Listwise Ranking

Loss function is based on the query and a list of documents.

- AdaRank
- ListNet
- ListMLE

AdaRank

Motivation: commonly used evaluation metrics are not differentiable. So it is not easy to optimize directly. AdaRank minimizes the exponential loss, E() below can be NDCG.

,

$$E(\pi_i, \mathbf{y}_i) \rightarrow exp(-E(\pi_i, \mathbf{y}_i))$$
$$\text{where } \pi_i \text{ is the predicted list}$$
$$\mathbf{y}_i \text{ is the ground truth list}$$

The usual AdaBoost algorithm applies afterwards.

Xu, J., Li, H.: Adarank: a boosting algorithm for information retrieval. In: Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2007), pp. 391–398 (2007)

ListNet / ListMLE

Map list of scores to a probability distribution by Plackett–Luce model.

- Permutation probability, where s() is the scoring function.

$$P_s(\pi) = \prod_{j=1}^{n} \frac{\phi(s_{\pi(j)})}{\sum_{k=j}^{n} \phi(s_{\pi(k)})}$$

- Top-1 probability

$$P_s(j) = \frac{\phi(s_j)}{\sum_{k=1}^{n} \phi(s_k)},$$

Loss function

- ListNet: K-L divergence or cross entropy loss between predicted probability and ground truth probability.
- ListMLE: negative log likelihood loss.

Cao, Z., Qin, T., Liu, T.Y., Tsai, M.F., Li, H.: Learning to rank: from pairwise approach to listwise approach. In: Proceedings of the 24th International Conference on Machine Learning (ICML 2007), pp. 129–136 (2007)

Summary of listwise ranking

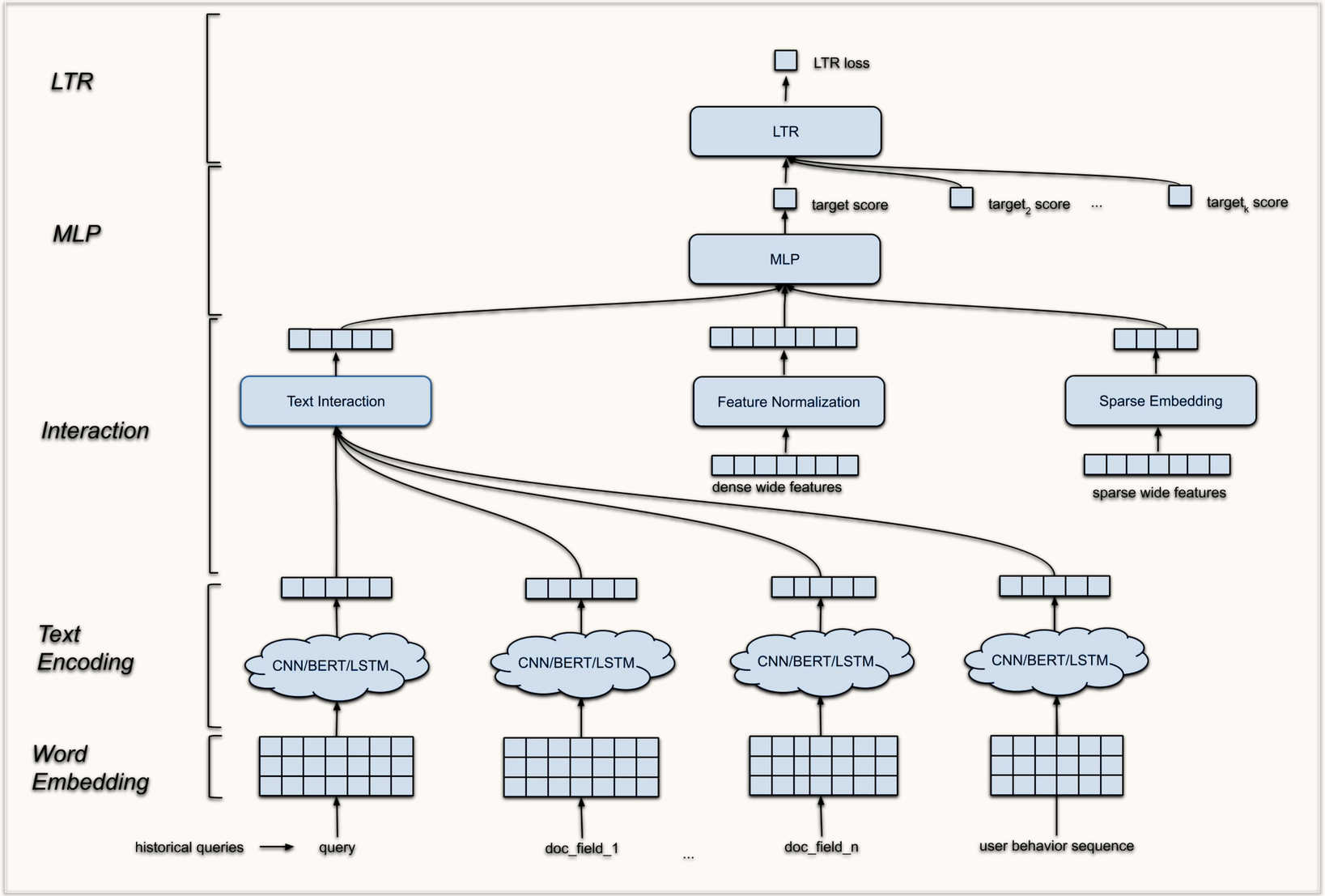
Pros

- Considers the entire list, uses more information for ranking.
- Usually offers the best performance.

Cons

- Higher complexity than algorithms in the other two categories.

DeText: a Deep Learning Ranking Framework



- Deep Learning + Ranking
- Supports pointwise, pairwise and listwise functions.
- Compatible with TF-ranking
- Automatic text feature incorporation
- Find more at https://github.com/linkedin/detext

LinkedIn

Learning to Rank

Hands-on: Generalized Deep Mixed Model and DeText

Mingzhou Zhou

Sandeep Jha

KDD 2020

Thank you