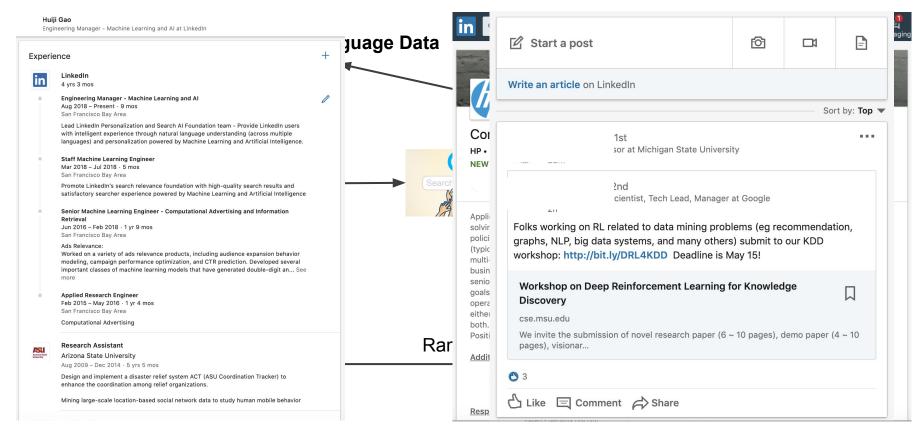


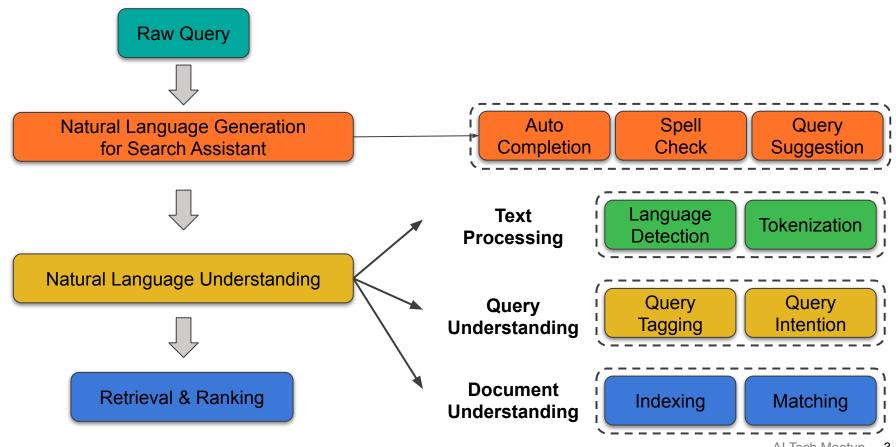
Deep Natural Language Processing in Search Systems

Weiwei Guo, Xiaowei Liu, Huiji Gao LinkedIn AI 05/09/2019

Natural Language Data in Search Systems



Natural Language Processing in Search Ecosystem



NLP in Search Systems: Challenges

Data Ambiguity

- Short query text
 - "abc"
- No strict syntax
 - "bing search engineer"
- Strong correlation to the searcher
 - "looking for new jobs"

Deep Semantics

- Representations for query & document w.r.t. search intent, entities, topics
 - "Engineering Openings" -> job posts

Deep NLP in Search: Challenges

Complicated Search Ecosystem

- Query suggestion affects both recall and precision in downstream retrieval and ranking.
- Query tagging needs to be compatible with indexing and align with ranking features.

Product Oriented Model Design

- Design deep NLP algorithms for specific search components
- Consider business rules, post filters, results blender, user experience, etc.

Online Latency

Serving deep NLP models with product latency restriction

Applying Deep NLP in Search

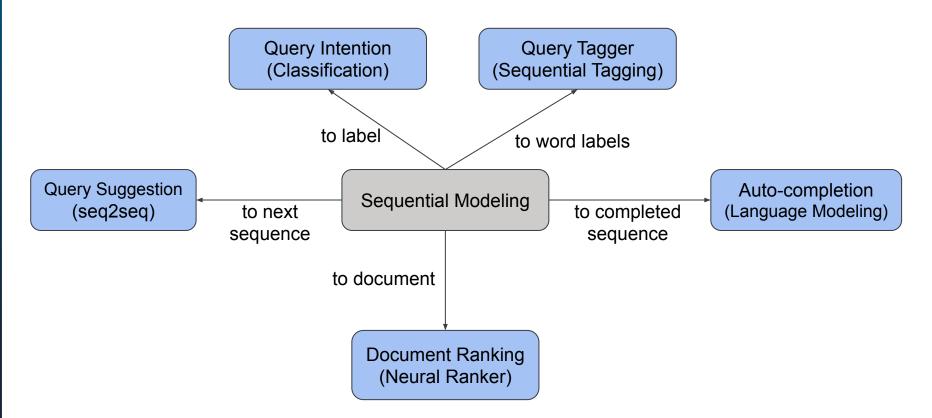
Feature Driven

Representation Learning
using features generated from deep learning models
e.g., word embedding

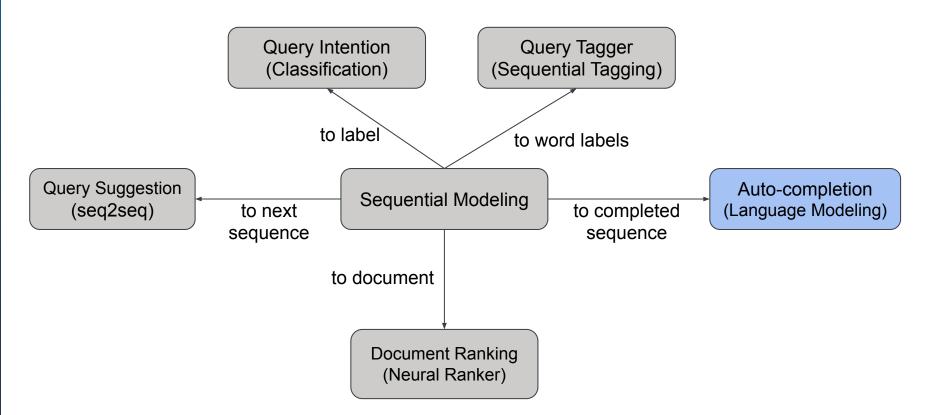
Model Driven

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

Deep Learning for Natural Language Processing



Deep Learning for Natural Language Processing



Natural Language Generation: Auto-Completion

softw

software engineer salary software engineer software software engineer jobs software developer Given a prefix, predict the completed query, rather than the completed word

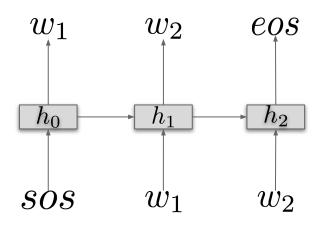
Auto-completion Challenges

- High requirement of latency
 - Have to adopt simple and fast models
- Traditional methods cannot encode powerful textual features
 - Usually the helpful feature is the query frequency

A Two-step Approach: Generation and Ranking

- Candidate Generation
 - Collect query frequency from search log
 - For any prefix, FST returns the most frequent completed queries
 - When a prefix is never seen, remove one word from beginning
 - e.g., "metamind sof" → "sof"
- Candidate Ranking
 - Neural Language Model serves as a scoring function

Auto-Completion: Neural Language Model as Scoring/Ranking



$$s(q) = \sum_{i} \log P(w_{i+1}|h_i)$$

Achieved 6x speedup with optimization

Auto-Completion Offline Experiments

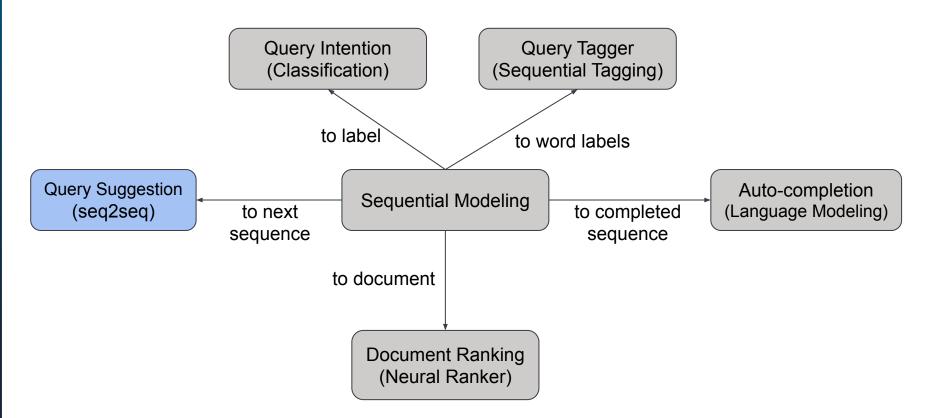
Public Data Set: AOL

Baseline: Most Popular Candidate (MPC), FST-backoff

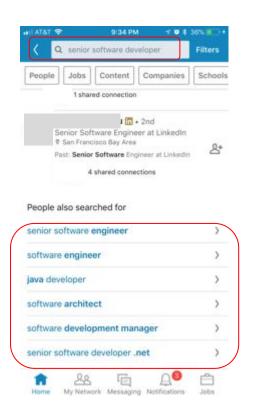
- Evaluation metrics: MRR, 4th place \rightarrow 0.25

Generation	Ranking	dev	test
MPC		18.097	17.032
FST-backoff		33.274 (+83.8%)	32.331 (+89.8%)
FST-backoff	neural	34.877 (+92.7%)	33.784 (+98.3%)

Deep Learning for Natural Language Processing

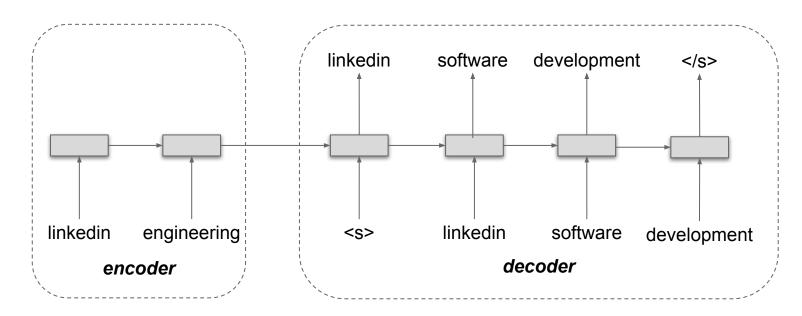


Natural Language Generation: Query Suggestion



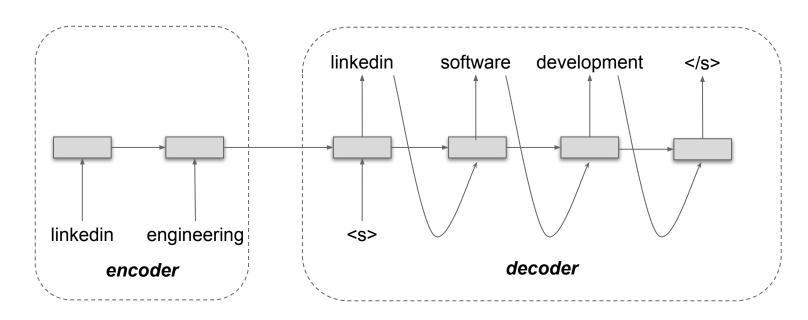
- Traditional frequency based methods
 - Collect <q1, q2> pairs from search log
 - Save the frequent pairs in a key-value store
- Lack of generalization
 - Purely string matching
 - Cannot handle unseen queries, rare words
- Seq2seq: capture query reformulation

Query Suggestion: Reformulate to Related Queries



- Training: the 2nd query is given
- Maximize $P(\mathbf{y}|\mathbf{x}) = \prod P(y_i|h_i)$

Query Suggestion: Reformulate to Related Queries



- Inference: the 2nd query is unknown
- Beam search instead of greedy search

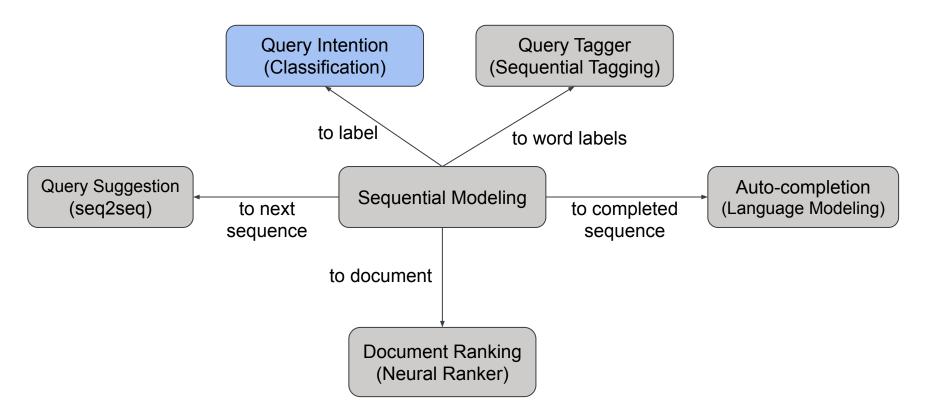
Query Suggestion: How to Handle Online Latency

- Latency too long for one query
- Make it parallel with search ranking

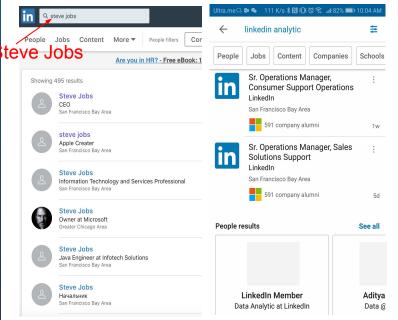
Online Performance

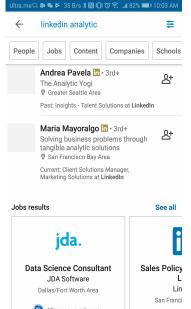
- English Market
 - Coverage: +80% Impressions, +26% CTR
 - +1% Total job application
- I18n Market
 - +3.2% Successful Searches
 - +28.6% First Order Actions

Deep Learning for Natural Language Processing



Natural Language Understanding: Query Intent





Motivation:

 To understand the task user wants to finish on LinkedIn

Challenges:

- Complicated Semantics
- Personalization

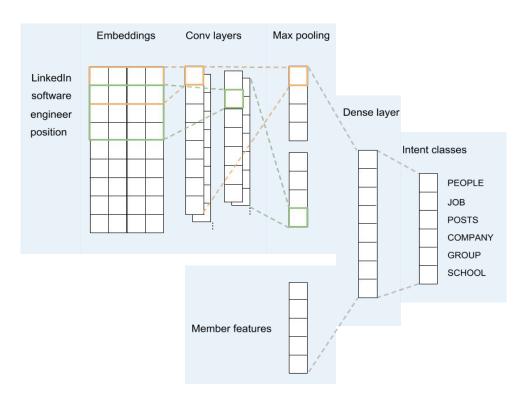
CNN Based Query Intention Model

CNN for Semantic Feature Extraction

- Word/query representations
- Generalization power
- Word n-gram patterns

Personalization

Member-level Features



Query Intent

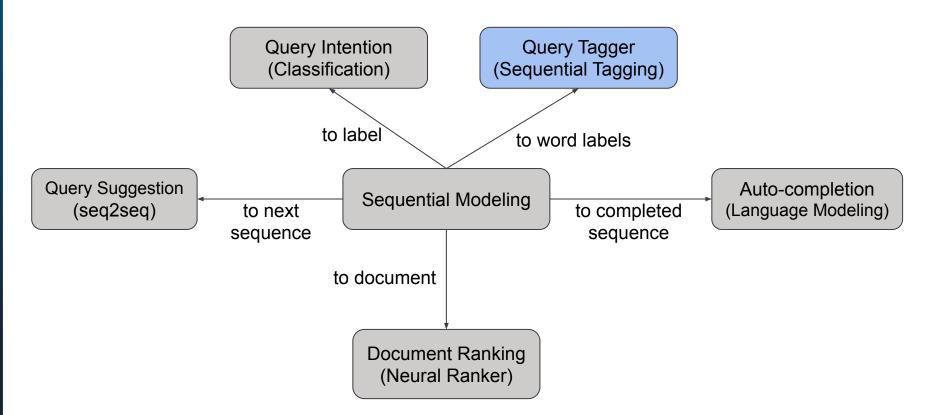
Offline results

	Overall Accuracy	F1 on PEOPLE	F1 on JOB	
LR (Baseline)	-	-	-	
LR + BOW	+1.3%	+4.1%	+0.8%	
CNN	+2.9%	+11.9%	+1.7%	

Online results

- + 0.65% JOB Ctr At 1 Serp
- + 0.90% Overall Cluster Ctr, + 4.03% Cluster Ctr Via Entity Click

Deep Learning for Natural Language Processing



Natural Language Understanding: Query Tagger

LinkedIn	software	engineer	data	scientist	jobs
CN	Т	Т	Т	Т	0
B-CN	В-Т	I-T	В-Т	I-T	0

B-CN: beginning of a company name

I-CN: Inside of a company name

B-T: beginning of a job title

I-T: Inside of a job title

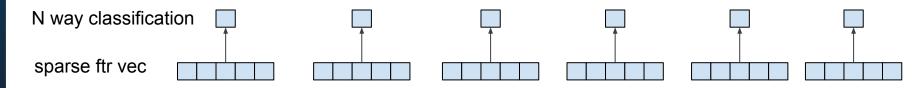
O: Not an entity

B-PN: beginning of person name

. . .

Query Tagger: Logistic Regression

LinkedIn	software	engineer	data	scientist	jobs
B-CN	В-Т	I-T	В-Т	I-T	0



ftr 0: whether the current word is "linkedin" ftr 1: whether the current word is "facebook"

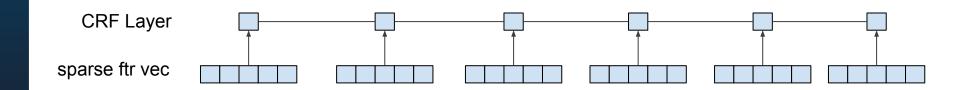
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ftr n: whether the next word is "software" ftr n+1: whether the next word is "linkedin"

. . . .

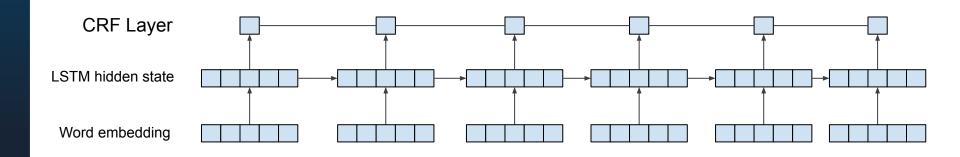
Query Tagger: CRF

LinkedIn	software	engineer	data	scientist	jobs
B-CN	В-Т	I-T	В-Т	I-T	0

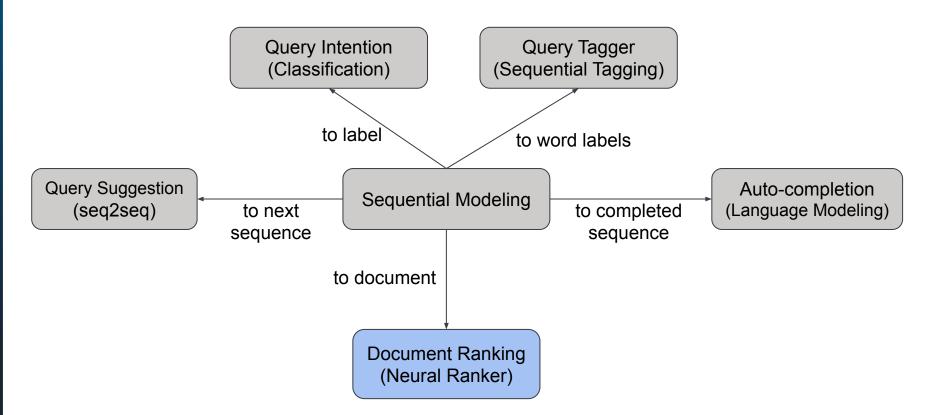


Query Tagger: CRF + LSTM

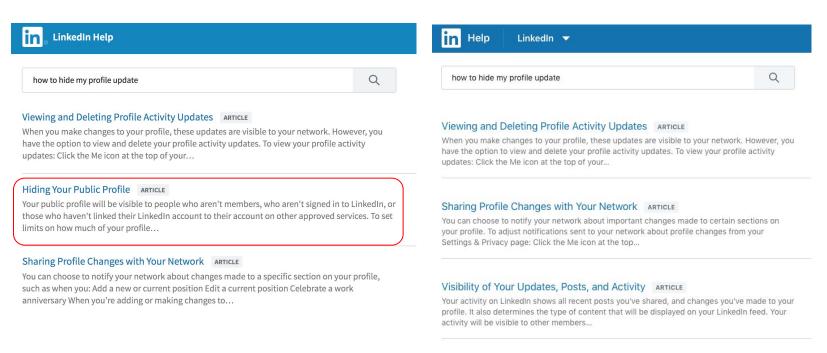
LinkedIn	software	engineer	data	scientist	jobs
B-CN	В-Т	I-T	В-Т	I-T	0



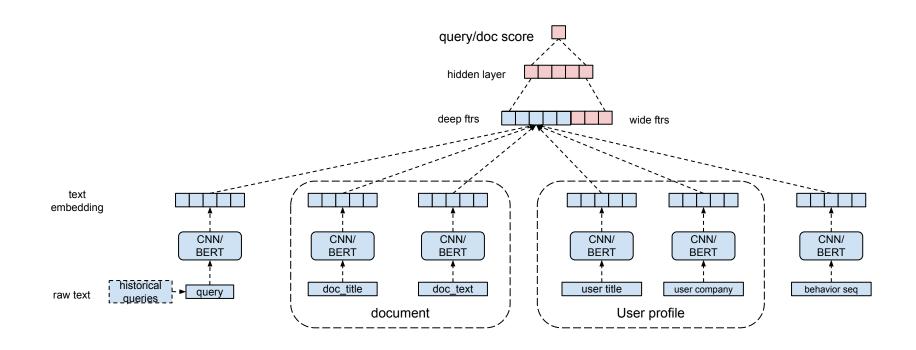
Deep Learning for Natural Language Processing



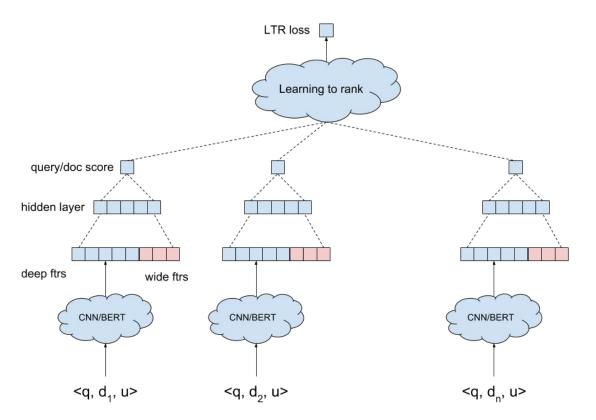
Natural Language Understanding: Document Ranking



Neural Ranking: Scoring a Query/Document Pair



Neural Ranking: Training



Offline Experiments

People Search Ranking (NDCG@10)		
Wide Features		
CNN	+1.32%	
BERT (google pretrained)	+1.52%	
BERT (linkedin pretrained)	+1.96%	

Online Experiments (100% Ramp)

- Help center ranking (BERT vs CNN)
 - +9.5% search ctr
 - +7% search clicks

Conclusions & Future Work

 Deep NLP technologies can power various search components directly with proper handling on challenges such as latency

 Design deep NLP technologies needs to consider the specific product properties as well as user experience

 Multilingual learning can be exploited for developing advanced deep NLP technologies

