

A Deep Look into Neural Ranking Models for Information Retrieval

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Abstract

Ranking models lie at the heart of research on information retrieval (IR). During the past decades, different techniques have been proposed for constructing ranking models, from traditional heuristic methods, probabilistic methods, to modern machine learning methods. Recently, with the advance of deep learning technology, we have witnessed a growing body of work in applying shallow or deep neural networks to the ranking problem in IR, referred to as neural ranking models in this paper. The power of neural ranking models lies in the ability to learn from the raw text inputs for the ranking problem to avoid many limitations of hand-crafted features. Neural networks have sufficient capacity to model complicated tasks, which is needed to handle the complexity of relevance estimation in ranking. Since there have been a large variety of neural ranking models proposed, we believe it is the right time to summarize the current status, learn from existing methodologies, and gain some insights for future development. In contrast to existing reviews, in this survey, we will take a deep look into the neural ranking models from different dimensions to analyze their underlying assumptions, major design principles, and learning strategies. We compare these models through benchmark tasks to obtain a comprehensive empirical understanding of the existing techniques. We will also discuss what is missing in the current literature and what are the promising and desired future directions.

Keywords: neural ranking model, information retrieval, survey

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1. Introduction

Information retrieval is a core task in many real-world applications, such as digital libraries, expert finding, Web search, and so on. Essentially, IR is the activity of obtaining some information resources relevant to an information need
5 from within large collections. As there might be a variety of relevant resources, the returned results are typically ranked with respect to some relevance notion. This ranking of results is a key difference of IR from other problems. Therefore, research on ranking models has always been at the heart of IR.

Many different ranking models have been proposed over the past decades,
10 including vector space models [1], probabilistic models [2], and learning to rank (LTR) models [3, 4]. Existing techniques, especially the LTR models, have already achieved great success in many IR applications, e.g., modern Web search engines like Google¹ or Bing². There is still, however, much room for improvement in the effectiveness of these techniques for more complex retrieval tasks.

15 In recent years, deep neural networks have led to exciting breakthroughs in speech recognition [5], computer vision [6, 7], and natural language processing (NLP) [8, 9]. These models have been shown to be effective at learning abstract representations from the raw input, and have sufficient model capacity to tackle difficult learning problems. Both of these are desirable properties for ranking
20 models in IR. On one hand, most existing LTR models rely on hand-crafted features, which are usually time-consuming to design and often over-specific in definition. It would be of great value if ranking models could learn the useful ranking features automatically. On the other hand, relevance, as a key notion in IR, is often vague in definition and difficult to estimate since relevance
25 judgments are based on a complicated human cognitive process. Neural models

¹<http://google.com>

²<http://bing.com>

with sufficient model capacity have more potential for learning such complicated tasks than traditional shallow models. Due to these potential benefits and along with the expectation that similar successes with deep learning could be achieved in IR [10], we have witnessed substantial growth of work in applying neural
30 networks for constructing ranking models in both academia and industry in recent years. Note that in this survey, we focus on neural ranking models for textual retrieval, which is central to IR, but not the only mode that neural models can be used for [11, 12].

Perhaps the first successful model of this type is the Deep Structured Semantic Model (DSSM) [13] introduced in 2013, which is a neural ranking model
35 that directly tackles the ad-hoc retrieval task. In the same year, Lu and Li [14] proposed DeepMatch, which is a deep matching method applied to the Community-based Question Answering (CQA) and micro-blog matching tasks. Note that at the same time or even before this work, there were a number of
40 studies focused on learning low-dimensional representations of texts with neural models [15, 16] and using them either within traditional IR models or with some new similarity metrics for ranking tasks. However, we would like to refer to those methods as representation learning models rather than neural ranking models, since they did not directly construct the ranking function with neural
45 networks. Later, between 2014 and 2015, work on neural ranking models began to grow, such as new variants of DSSM [13], ARC I and ARC II [17], MatchPyramid [18], and so on. Most of this research focused on short text ranking tasks, such as TREC QA tracks and Microblog tracks [19]. Since 2016, the study of neural ranking models has bloomed, with significant work volume, deeper and
50 more rigorous discussions, and much wider applications [20]. For example, researchers began to discuss the practical effectiveness of neural ranking models on different ranking tasks [21, 22]. Neural ranking models have been applied to ad-hoc retrieval [23, 24], community-based QA [25], conversational search [26], and so on. Researchers began to go beyond the architecture of neural ranking
55 models, paying attention to new training paradigms of neural ranking models [27], alternate indexing schemes for neural representations [28], integration of

external knowledge [29, 30], and other novel uses of neural approaches for IR tasks [31, 32].

Up to now, we have seen exciting progress on neural ranking models. In academia, several neural ranking models learned from scratch can already outperform state-of-the-art LTR models with tens of hand-crafted features [33, 34]. Workshops and tutorials on this topic have attracted extensive interest in the IR community [10, 35]. Standard benchmark datasets [36, 37], evaluation tasks [38], and open-source toolkits [39] have been created to facilitate research and rigorous comparison. Meanwhile, in industry, we have also seen models such as DSSM put into a wide range of practical usage in the enterprise [40]. Neural ranking models already generate the most important features for modern search engines. However, beyond these exciting results, there is still a long way to go for neural ranking models: 1) Neural ranking models have not had the level of breakthroughs achieved by neural methods in speech recognition or computer vision; 2) There is little understanding and few guidelines on the design principles of neural ranking models; 3) We have not identified the special capabilities of neural ranking models that go beyond traditional IR models. Therefore, it is the right moment to take a look back, summarize the current status, and gain some insights for future development.

There have been some related surveys on neural approaches to IR (neural IR for short). For example, Onal et al.[20] reviewed the current landscape of neural IR research, paying attention to the application of neural methods to different IR tasks. Mitra and Craswell [41] gave an introduction to neural information retrieval. In their booklet, they talked about fundamentals of text retrieval, and briefly reviewed IR methods employing pre-trained embeddings and neural networks. In contrast to this work, this survey does not try to cover every aspect of neural IR, but will focus on and take a deep look into ranking models with deep neural networks. Specifically, we formulate the existing neural ranking models under a unified framework, and review them from different dimensions to understand their underlying assumptions, major design principles, and learning strategies. We also compare representative neural ranking models

through benchmark tasks to obtain a comprehensive empirical understanding. We hope these discussions will help researchers in neural IR learn from previous
90 successes and failures, so that they can develop better neural ranking models in the future. In addition to the model discussion, we also introduce some trending topics in neural IR, including indexing schema, knowledge integration, visualized learning, contextual learning and model explanation. Some of these topics are important but have not been well addressed in this field, while others are
95 very promising directions for future research.

In the following, we will first introduce some typical textual IR tasks addressed by neural ranking models in Section 2. We then provide a unified formulation of neural ranking models in Section 3. From section 4 to 6, we review the existing models with regard to different dimensions as well as making
100 empirical comparisons between them. We discuss trending topics in Section 7 and conclude the paper in Section 8.

2. Major Applications of Neural Ranking Models

In this section, we describe several major textual IR applications where neural ranking models have been adopted and studied in the literature, including
105 ad-hoc retrieval, question answering, community question answering, and automatic conversation. There are other applications where neural ranking models have been or could be applied, e.g., product search [12], sponsored search [42], and so on. However, due to page limitations, we will not include these tasks in this survey.

110 2.1. *Ad-hoc Retrieval*

Ad-hoc retrieval is a classic retrieval task in which the user specifies his/her information need through a query which initiates a search (executed by the information system) for documents that are likely to be relevant to the user. The term *ad-hoc* refers to the scenario where documents in the collection remain
115 relatively static while new queries are submitted to the system continually [43].

The retrieved documents are typically returned as a ranking list through a ranking model where those at the top of the ranking are more likely to be relevant.

There has been a long research history on ad-hoc retrieval, with several well
120 recognized characteristics and challenges associated with the task. A major
characteristic of ad-hoc retrieval is the heterogeneity of the query and the doc-
uments. The query comes from a search user with potentially unclear intent
and is usually very short, ranging from a few words to a few sentences [41].
The documents are typically from a different set of authors and have longer
125 text length, ranging from multiple sentences to many paragraphs. Such hetero-
geneity leads to the critical vocabulary mismatch problem [44, 45]. Semantic
matching, meaning matching words and phrases with similar meanings, could
alleviate the problem, but exact matching is indispensable especially with rare
terms [21]. Such heterogeneity also leads to diverse relevance patterns. Different
130 hypotheses, e.g. verbosity hypothesis and scope hypothesis [46], have been pro-
posed considering the matching of a short query against a long document. The
relevance notion in ad-hoc retrieval is inherently vague in definition and highly
user dependent, making relevance assessment a very challenging problem.

For the evaluation of different neural ranking models on the ad-hoc retrieval
135 task, a large variety of TREC collections have been used. Specifically, retrieval
experiments have been conducted over neural ranking models based on TREC
collections such as Robust [21, 18], ClueWeb [21], GOV2 [33, 34] and Microblog
[33], as well as logs such as the AOL log [27] and the Bing Search log [13, 47, 48,
23]. Recently, a new large scale dataset has been released, called the NTCIR
140 WWW Task [49], which is suitable for experiments on neural ranking models.

2.2. Question Answering

Question-answering (QA) attempts to automatically answer questions posed
by users in natural languages based on some information resources. The ques-
tions could be from a closed or open domain [50], while the information re-
145 sources could vary from structured data (e.g., knowledge base) to unstructured

data (e.g., documents or Web pages) [51]. There have been a variety of task formats for QA, including multiple-choice selection [52], answer passage/sentence retrieval [53, 37], answer span locating [54], and answer synthesizing from multiple sources [55]. In this survey, we focus on answer passage/sentence retrieval as it can be viewed as a typical IR problem. Hereafter, we will refer to this specific task as QA for simplicity..

Compared with ad-hoc retrieval, QA shows reduced heterogeneity between the question and the answer passage/sentence. On one hand, the question is usually in natural language, which is longer than keyword queries and clearer in intent description. On the other hand, the answer passages/sentences are usually much shorter text spans than documents (e.g., the answer passage length of WikiPassageQA data is about 133 words [56]), leading to more concentrated topics/semantics. However, vocabulary mismatch is still a basic problem in QA. The notion of relevance is relatively clear in QA, i.e., whether the target passage/sentence answers the question, but assessment is challenging. Ranking models need to capture the patterns expected in the answer passage/sentence based on the intent of the question, such as the matching of the context words, the existence of the expected answer type, and so on.

For the evaluation of QA tasks, several benchmark data sets have been developed, including TREC QA [53], WikiQA [37], WebAP [57, 58], InsuranceQA [59], WikiPassageQA [56] and MS MARCO [36]. A variety of neural ranking models [60, 19, 61, 25, 14] have been tested on these data sets.

2.3. Community Question Answering

Community question answering (CQA) aims to find answers to users' questions based on existing QA resources in CQA websites, such as Quora ³, Yahoo! Answers ⁴, Stack Overflow ⁵, and Zhihu ⁶. As a retrieval task, CQA can be fur-

³<https://www.quora.com/>

⁴<https://answers.yahoo.com>

⁵<https://www.stackoverflow.com>

⁶<https://zhihu.com>

ther divided into two categories. The first is to directly retrieval answers from the answer pool, which is similar to the above QA task with some additional user behavioral data (e.g., upvotes/downvotes) [62]. So we will not discuss this
175 format here again. The second is to retrieve similar questions from the question pool, based on the assumption that answers to similar question could answer new questions. Unless otherwise noted, we will refer to the second task format as CQA.

Since it involves the retrieval of similar questions, CQA is significantly dif-
180 ferent from the previous two tasks due to the homogeneity between the input question and target question. Specifically, both input and target questions are short natural language sentences (e.g. the question length in Yahoo! Answers is between 9 and 10 words on average [63]), describing users' information needs. Relevance in CQA refers to semantic equivalence/similarity, which is clear and
185 symmetric in the sense that the two questions are exchangeable in the relevance definition. However, vocabulary mismatch is still a challenging problem as both questions are short and there exist different expressions for the same intent.

For evaluation of the CQA task, a large variety of data sets have been re-
leased for research. The well-known data sets include the Quora Dataset⁷,
190 Yahoo! Answers Dataset [25] and SemEval-2017 Task3 [64]. The recent proposed datasets include CQADupStack⁸ [65], ComQA⁹ [66] and LinkSO [67]. A variety of neural ranking models [68, 18, 69, 70, 25] have been tested on these data sets.

2.4. Automatic Conversation

195 Automatic conversation (AC) aims to create an automatic human-computer dialog process for the purpose of question answering, task completion, and social chat (i.e., chit-chat) [71]. In general, AC could be formulated either as an IR problem that aims to rank/select a proper response from a dialog repository [72]

⁷<https://data.quora.com/First-Quora-Dataset-Release-Question-Pairs>

⁸<https://github.com/D1Doris/CQADupStack>

⁹<http://qa.mpi-inf.mpg.de/comqa>

or a generation problem that aims to generate an appropriate response with re-
spect to the input utterance [73]. In this paper, we restrict AC to the social chat
200 task with the IR formulation, since question answering has already been covered
in the above QA task and task completion is usually not taken as an IR prob-
lem. From the perspective of conversation context, the IR-based AC could be
further divided into single-turn conversation[74] or multi-turn conversation [75].

205 When focusing on social chat, AC also shows homogeneity similar to CQA.
That is, both the input utterance and the response are short natural language
sentences (e.g., the utterance length of Ubuntu Dialog Corpus is between 10
to 11 words on average and the median conversation length of it is 6 words
[76]). Relevance in AC refers to certain semantic correspondence (or coherent
210 structure) which is broad in definition, e.g., given an input utterance “OMG I
got myopia at such an ‘old’ age”, the response could range from general (e.g.,
“Really?”) to specific (e.g., “Yeah. Wish a pair of glasses as a gift”) [26]. There-
fore, vocabulary mismatch is no longer the central challenge in AC, as we can
see from the example that a good response does not require semantic matching
215 between the words. Instead, it is critical to model correspondence/coherence
and avoid general trivial responses.

For the evaluation of different neural ranking models on the AC task, several
conversation collections have been collected from social media such as forums,
Twitter and Weibo. Specifically, experiments have been conducted over neural
220 ranking models based on collections such as Ubuntu Dialog Corpus (UDC) [75,
77, 78], Sina Weibo dataset [74, 26, 79, 80], MSDialog [81, 30, 82] and the
”campaign” NTCIR STC [83].

3. A Unified Model Formulation

Neural ranking models are mostly studied within the LTR framework. In
225 this section, we give a unified formulation of neural ranking models from a
generalized view of LTR problems.

Suppose that \mathcal{S} is the *generalized* query set, which could be the set of search

queries, natural language questions or input utterances, and \mathcal{T} is the *generalized* document set, which could be the set of documents, answers or responses. Suppose that $\mathcal{Y} = \{1, 2, \dots, l\}$ is the label set where labels represent grades. There exists a total order between the grades $l \succ l-1 \succ \dots \succ 1$, where \succ denotes the order relation. Let $s_i \in \mathcal{S}$ be the i -th query, $T_i = \{t_{i,1}, t_{i,2}, \dots, t_{i,n_i}\} \in \mathcal{T}$ be the set of documents associated with the query s_i , and $\mathbf{y}_i = \{y_{i,1}, y_{i,2}, \dots, y_{i,n_i}\}$ be the set of labels associated with query s_i , where n_i denotes the size of T_i and \mathbf{y}_i and $y_{i,j}$ denotes the relevance degree of $t_{i,j}$ with respect to s_i . Let \mathcal{F} be the function class and $f(s_i, t_{i,j}) \in \mathcal{F}$ be a ranking function which associates a relevance score with a query-document pair. Let $L(f; s_i, t_{i,j}, \mathbf{y}_{i,j})$ be the loss function defined on prediction of f over the query-document pair and their corresponding label. So a generalized LTR problem is to find the optimal ranking function f^* by minimizing the loss function over some labeled dataset

$$f^* = \arg \min \sum_i \sum_j L(f; s_i, t_{i,j}, y_{i,j}) \quad (1)$$

Without loss of generality, the ranking function f could be further abstracted by the following unified formulation

$$f(s, t) = g(\psi(s), \phi(t), \eta(s, t)) \quad (2)$$

where s and t are two input texts, ψ, ϕ are representation functions which extract features from s and t respectively, η is the interaction function which extracts features from (s, t) pair, and g is the evaluation function which computes the relevance score based on the feature representations.

Note that for traditional LTR approaches [3], functions ψ, ϕ and η are usually set to be fixed functions (i.e., manually defined feature functions). The evaluation function g can be any machine learning model, such as logistic regression or gradient boosting decision tree, which could be learned from the training data. For neural ranking models, in most cases, all the functions ψ, ϕ, η and g are encoded in the network structures so that all of them can be learned from training data.

In traditional LTR approaches, the inputs s and t are usually raw texts. In
255 neural ranking models, we consider that the inputs could be either raw texts or
word embeddings. In other words, embedding mapping is considered as a basic
input layer, not included in ψ , ϕ and η .

4. Model Architecture

Based on the above unified formulation, here we review existing neural rank-
260 ing model architectures to better understand their basic assumptions and design
principles.

4.1. Symmetric vs. Asymmetric Architectures

Starting from different underlying assumptions over the input texts s and
 t , two major architectures emerge in neural ranking models, namely symmetric
265 architecture and asymmetric architecture.

Symmetric Architecture: The inputs s and t are assumed to be homo-
geneous, so that symmetric network structure could be applied over the inputs.
Note here symmetric structure means that the inputs s and t can exchange
their positions in the input layer without affecting the final output. Specifically,
270 there are two representative symmetric structures, namely siamese networks and
symmetric interaction networks.

Siamese networks literally imply symmetric structure in the network ar-
chitecture. Representative models include DSSM [13], CLSM [47] and LSTM-
RNN [48]. For example, DSSM represents two input texts with a unified pro-
275 cess including the letter-trigram mapping followed by the multi-layer perceptron
(MLP) transformation, i.e., function ϕ is the same as function ψ . After that a
cosine similarity function is applied to evaluate the similarity between the two
representations, i.e., function g is symmetric. Similarly, CLSM [47] replaces the
representation functions ψ and ϕ by two identical convolutional neural networks
280 (CNNs) in order to capture the local word order information. LSTM-RNN [48]
replaces ψ and ϕ by two identical long short-term memory (LSTM) networks in
order to capture the long-term dependence between words.

Symmetric interaction networks, as shown by the name, employ a symmetric interaction function to represent the inputs. Representative models include
285 DeepMatch [14], Arc-II [17], MatchPyramid [18] and Match-SRNN [69]. For example, Arc-II defines an interaction function η over s and t by computing similarity (i.e., weighted sum) between every n-gram pair from s and t , which is symmetric in nature. After that, several convolutional and max-pooling layers are leveraged to obtain the final relevance score, which is also symmetric over
290 s and t . MatchPyramid defines a symmetric interaction function η between every word pair from s and t to capture fine-grained interaction signals. It then leverages a symmetric evaluation function g , i.e., several 2D CNNs and a dynamic pooling layer, to produce the relevance score. A similar process can be found in DeepMatch and Match-SRNN.

295 Symmetric architectures, with the underlying homogeneous assumption, can fit well with the CQA and AC tasks, where s and t usually have similar lengths and similar forms (i.e., both are natural language sentences). They may sometimes work for the ad-hoc retrieval or QA tasks if one only uses document titles/snippets [13] or short answer sentences [61] to reduce the heterogeneity
300 between the two inputs.

Asymmetric Architecture: The inputs s and t are assumed to be heterogeneous, so that asymmetric network structures should be applied over the inputs. Note here asymmetric structure means if we change the position of the inputs s and t in the input layer, we will obtain totally different output. Asym-
305 metric architectures have been introduced mainly in the ad-hoc retrieval task [13, 33], due to the inherent heterogeneity between the query and the document as discussed in Section 2.1. Such structures may also work for the QA task where answer passages are ranked against natural language questions [84].

Here we take the ad-hoc retrieval scenario as an example to analyze the
310 asymmetric architecture. We find there are three major strategies used in the asymmetric architecture to handle the heterogeneity between the query and the document, namely query split, document split, and joint split.

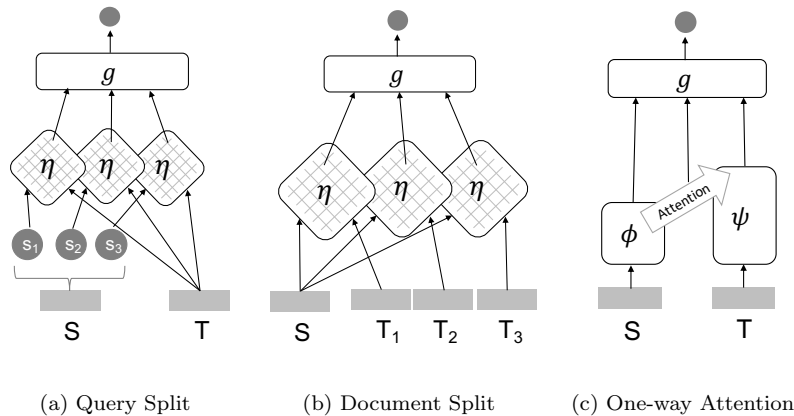


Figure 1: Three types of Asymmetric Architecture.

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 • *Query split* is based on the assumption that most queries in ad-hoc retrieval are keyword based, so that we can split the query into terms to match against the document, as illustrated in Figure 1(a). A typical model based on this strategy is DRMM [21]. DRMM splits the query into terms and defines the interaction function η as the matching histogram mapping between each query term and the document. The evaluation function g consists of two parts, i.e., a feed-forward network for term-level relevance computation and a gating network for score aggregation. Obviously such a process is asymmetric with respect to the query and the document. K-NRM [85] also belongs to this type of approach. It introduces a kernel pooling function to approximate matching histogram mapping to enable end-to-end learning.
- 325
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 • *Document split* is based on the assumption that a long document could be partially relevant to a query under the scope hypothesis [2], so that we split the document to capture fine-grained interaction signals rather than treat it as a whole, as depicted in Figure 1(b). A representative model based on this strategy is HiNT [34]. In HiNT, the document is first split into passages using a sliding window. The interaction function η is defined as the cosine similarity and exact matching between the query and each passage. The evaluation function g includes the local matching layers and

global decision layers.

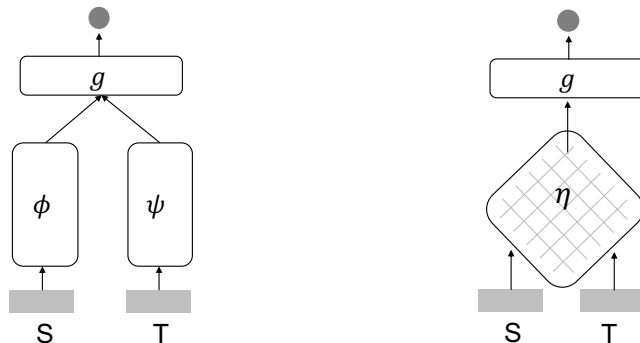
- *Joint split*, by its name, uses both assumptions of query split and document split. A typical model based on this strategy is DeepRank [33]. Specifically, DeepRank splits the document into term-centric contexts with respect to each query term. It then defines the interaction function η between the query and term-centric contexts in several ways. The evaluation function g includes three parts, i.e., term-level computation, term-level aggregation, and global aggregation. Similarly, PACRR [24] takes the query as a set of terms and splits the document using the sliding window as well as the first-k term window.

In addition, in neural ranking models applied for QA, there is another popular strategy leading the asymmetric architecture. We name it *one-way attention mechanism* which typically leverages the question representation to obtain the attention over candidate answer words in order to enhance the answer representation, as illustrated in Figure 1(c). For example, IARNN [86] and CompAgg [87] get the attentive answer representation sequence that weighted by the question sentence representation.

4.2. Representation-focused vs. Interaction-focused Architectures

Based on different assumptions over the features (extracted by the representation function ϕ, ψ or the interaction function η) for relevance evaluation, we can divide the existing neural ranking models into another two categories of architectures, namely representation-focused architecture and interaction-focused architecture, as illustrated in Figure 2. There is a hybrid architecture which combines both. However, since it is a natural extension and there is limited work in this direction [23, 86], we will not discuss it separately.

Representation-focused Architecture: The underlying assumption of this type of architecture is that relevance depends on compositional meaning of the input texts. Therefore, models in this category usually define complex representation functions ϕ and ψ (i.e., deep neural networks), but no interaction



(a) Representation-focused

(b) Interaction-focused

Figure 2: Representation-focused and Interaction-focused Architectures.

function η , to obtain high-level representations of the inputs s and t , and uses some simple evaluation function g (e.g. cosine function or MLP) to produce the final relevance score. Different deep network structures have been applied for ϕ and ψ , including fully-connected networks, convolutional networks and recurrent networks.

- To our best knowledge, DSSM [13] is the only one that uses the fully-connected network for the functions ϕ and ψ , which has been described in Section 4.1.
- Convolutional networks have been used for ϕ and ψ in Arc-I [17], CNTN [25] and CLSM [47]. Take Arc-I as an example, stacked 1D convolutional layers and max pooling layers are applied on the input texts s and t to produce their high-level representations respectively. Arc-I then concatenates the two representations and applies an MLP as the evaluation function g . The main difference between CNTN and Arc-I is the function g , where the neural tensor layer is used instead of the MLP. The description on CLSM could be found in Section 4.1.
- Recurrent networks have been used for ϕ and ψ in LSTM-RNN [48] and MV-LSTM [88]. LSTM-RNN uses a one-directional LSTM as ϕ and ψ to encode the input texts, which has been described in Section 4.1. MV-

LSTM employs a bi-directional LSTM instead to encode the input texts. Then, the top-k strong matching signals between the two high-level representations are fed to an MLP to generate the relevance score.

By evaluating relevance based on high-level representations of each input text, representation-focused architecture better fits tasks with the global matching requirement [21]. This architecture is also more suitable for tasks with short input texts (since it is often difficult to obtain good high-level representations of long texts). Tasks with these characteristics include CQA and AC as shown in Section 2. Moreover, models in this category are efficient for online computation, since one can pre-calculate representations of the texts offline once ϕ and ψ have been learned.

Interaction-focused Architecture: The underlying assumption of this type of architecture is that relevance is in essence about the relation between the input texts, so it would be more effective to directly learn from interactions rather than from individual representations. Models in this category thus define the interaction function η rather than the representation functions ϕ and ψ , and use some complex evaluation function g (i.e., deep neural networks) to abstract the interaction and produce the relevance score. Different interaction functions have been proposed in literature, which could be divided into two categories, namely non-parametric interaction functions and parametric interaction functions.

- *Non-parametric interaction functions* are functions that reflect the closeness or distance between inputs without learnable parameters. In this category, some are defined over each pair of input word vectors, such as binary indicator function [18, 33], cosine similarity function [18, 61, 33], dot-product function [18, 33, 34] and radial-basis function [18]. The others are defined between a word vector and a set of word vectors, e.g. the matching histogram mapping in DRMM [21] and the kernel pooling layer in K-NRM [85].
- *Parametric interaction functions* are adopted to learn the similarity/distance

function from data. For example, Arc-II [17] uses 1D convolutional layer for the interaction between two phrases. Match-SRNN [69] introduces the neural tensor layer to model complex interactions between input words. In general, parametric interaction functions are adopted when there is sufficient training data since they bring the model flexibility at the expense of larger model complexity.

By evaluating relevance directly based on interactions, the interaction-focused architecture can fit most IR tasks in general. Moreover, by using detailed interaction signals rather than high-level representations of individual texts, this architecture could better fit tasks that call for specific matching patterns (e.g., exact word matching) and diverse matching requirement [21], e.g., ad-hoc retrieval. This architecture also better fit tasks with heterogeneous inputs, e.g., ad-hoc retrieval and QA, since it circumvents the difficulty of encoding long texts. Unfortunately, models in this category are not efficient for online computation, since the interaction function η cannot be pre-calculated until we see the input pair (s, t) .

4.3. Single-granularity vs. Multi-granularity Architecture

The final relevance score is produced by the evaluation function g , which takes the features from ϕ , ψ , and η as input for estimation. Based on different assumptions on the estimation process for relevance, we can divide existing neural ranking models into two categories, namely single-granularity models and multi-granularity models.

Single-granularity Architecture: The underlying assumption of the single-granularity architecture is that relevance can be evaluated based on the high-level features extracted by ϕ , ψ and η from the single-form text inputs. Under this assumption, the representation functions ϕ , ψ and the interaction function η are actually viewed as black-boxes to the evaluation function g . Therefore, g only takes their final outputs for relevance computation. Meanwhile, the inputs s and t are simply viewed a set/sequence of words or word embeddings without any additional language structures.

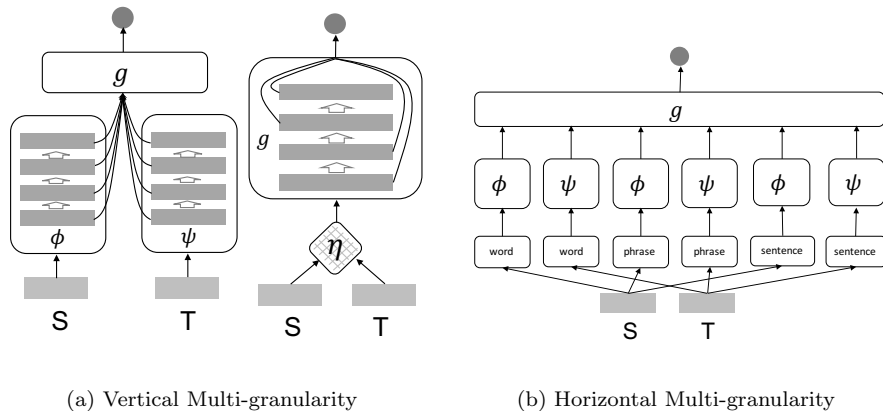


Figure 3: Multi-granularity Architectures.

Obviously, the assumption underlying the single-granularity architecture is very simple and basic. Many neural ranking models fall in this category, with either symmetric (e.g., DSSM and MatchPyramid) or asymmetric (e.g., DRMM and HiNT) architectures, either representation-focused (e.g., ARC-I and MV-LSTM) or interaction-focused (e.g., K-NRM and Match-SRNN).

Multi-granularity Architecture: The underlying assumption of the multi-granularity architecture is that relevance estimation requires multiple granularities of features, either from different-level feature abstraction or based on different types of language units of the inputs. Under this assumption, the representation functions ϕ , ψ and the interaction function η are no longer black-boxes to g , and we consider the language structures in s and t . We can identify two basic types of multi-granularity, namely vertical multi-granularity and horizontal multi-granularity, as illustrated in Figure 3.

- *Vertical multi-granularity* takes advantage of the hierarchical nature of deep networks so that the evaluation function g could leverage different-level abstraction of features for relevance estimation. For example, In MultigranCNN [89], the representation functions ψ and ϕ are defined as two CNN networks to encode the input texts respectively, and the evaluation function g takes the output of each layer for relevance estimation. MACM [90] builds a CNN over the interaction matrix from η , uses MLP

to generate a layer-wise score for each abstraction level of the CNN, and aggregates all the layers' scores for the final relevance estimation.

- *Horizontal multi-granularity* is based on the assumption that language has intrinsic structures (e.g., phrases or sentences), and we shall consider different types of language units, rather than simple words, as inputs for better relevance estimation. Models in this category typically enhance the inputs by extending it from words to phrases/n-grams or sentences, apply certain single-granularity architectures over each input form, and aggregate all the granularity for final relevance output. For example, in [91], a CNN and an LSTM are applied to obtain the character-level, word-level, and sentence-level representations of the inputs, and each level representations are then interacted and aggregated by the evaluation function g to produce the final relevance score. Similar ideas can be found in Conv-KNRM [84] and MIX [92].

As we can see, the multi-granularity architecture is a natural extension of the single-granularity architecture, which takes into account the inherent language structures and network structures for enhanced relevance estimation. With multi-granularity features extracted, models in this category are expected to better fit tasks that require fine-grained matching signals for relevance computation, e.g., ad-hoc retrieval [84] and QA [92]. However, the enhanced model capability is often reached at the expense of larger model complexity.

5. Model Learning

Beyond the architecture, in this section, we review the major learning objectives and training strategies adopted by neural ranking models for comprehensive understanding.

5.1. Learning objective

Similar to other LTR algorithms, the learning objective of neural ranking models can be broadly categorized into three groups: *pointwise*, *pairwise*, and

listwise. In this section, we introduce a couple of popular ranking loss functions
 490 in each group, and discuss their unique advantages and disadvantages for the
 applications of neural ranking models in different IR tasks.

5.1.1. Pointwise Ranking Objective

The idea of pointwise ranking objectives is to simplify a ranking problem to
 a set of classification or regression problems. Specifically, given a set of query-
 495 document pairs $(s_i, t_{i,j})$ and their corresponding relevance annotation $y_{i,j}$, a
 pointwise learning objective tries to optimize a ranking model by requiring it to
 directly predict $y_{i,j}$ for $(s_i, t_{i,j})$. In other words, the loss functions of pointwise
 learning objectives are computed based on each (s, t) pair independently. This
 can be formulated as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = \sum_i \sum_j L(y_{i,j}, f(s_i, t_{i,j})) \quad (3)$$

500 For example, one of the most popular pointwise loss functions used in neural
 ranking models is *Cross Entropy*:

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = - \sum_i \sum_j y_{i,j} \log(f(s_i, t_{i,j})) + (1 - y_{i,j}) \log(1 - f(s_i, t_{i,j})) \quad (4)$$

where $y_{i,j}$ is a binary label or annotation with probabilistic meanings (e.g.,
 clickthrough rate), and $f(s_i, t_{i,j})$ needs to be rescaled into the range of 0 to 1
 (e.g., with a sigmoid function $\sigma(x) = \frac{1}{1+\exp(-x)}$). Example applications include
 505 the Convolutional Neural Network for question answering [19]. There are other
 pointwise loss functions such as *Mean Squared Error* for numerical labels, but
 they are more commonly used in recommendation tasks.

The advantages of pointwise ranking objectives are two-fold. First, pointwise
 ranking objectives are computed based on each query-document pair $(s_i, t_{i,j})$
 510 separately, which makes it simple and easy to scale. Second, the outputs of
 neural models learned with pointwise loss functions often have real meanings
 and value in practice. For instance, in sponsored search, a model learned with
 cross entropy loss and clickthrough rates can directly predict the probability of

user clicks on search ads, which is more important than creating a good result
 515 list in some application scenarios.

In general, however, pointwise ranking objectives are considered to be less
 effective in ranking tasks. Because pointwise loss functions consider no docu-
 ment preference or order information, they do not guarantee to produce the best
 ranking list when the model loss reaches the global minimum. Therefore, better
 520 ranking paradigms that directly optimize document ranking based on pairwise
 loss functions and listwise loss functions have been proposed for LTR problems.

5.1.2. Pairwise Ranking Objective

Pairwise ranking objectives focus on optimizing the relative preferences be-
 tween documents rather than their labels. In contrast to pointwise methods
 525 where the final ranking loss is the sum of loss on each document, pairwise loss
 functions are computed based on the permutations of all possible document
 pairs [93]. It usually can be formalized as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = \sum_i \sum_{(j,k), y_{i,j} > y_{i,k}} L(f(s_i, t_{i,j}) - f(s_i, t_{i,k})) \quad (5)$$

where $t_{i,j}$ and $t_{i,k}$ are two documents for query s_i and $t_{i,j}$ is preferable comparing
 to $t_{i,k}$ (i.e., $y_{i,j} > y_{i,k}$). For instance, a well-known pairwise loss function is *Hingle*
 530 *loss*:

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = \sum_i \sum_{(j,k), y_{i,j} > y_{i,k}} \max(0, 1 - f(s_i, t_{i,j}) + f(s_i, t_{i,k})) \quad (6)$$

Hingle loss has been widely used in the training of neural ranking models such
 as DRMM [21] and K-NRM [85]. Another popular pairwise loss function is the
 pairwise cross entropy defined as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = - \sum_i \sum_{(j,k), y_{i,j} > y_{i,k}} \log \sigma(f(s_i, t_{i,j}) - f(s_i, t_{i,k})) \quad (7)$$

where $\sigma(x) = \frac{1}{1 + \exp(-x)}$. Pairwise cross entropy is first proposed in RankNet by
 535 Burges et al. [94], which is considered to be one of the initial studies on applying
 neural network techniques to ranking problems.

Ideally, when pairwise ranking loss is minimized, all preference relationships between documents should be satisfied and the model will produce the optimal result list for each query. This makes pairwise ranking objectives effective in many tasks where performance is evaluated based on the ranking of relevant documents. In practice, however, optimizing document preferences in pairwise methods does not always lead to the improvement of final ranking metrics due to two reasons: (1) it is impossible to develop a ranking model that can correctly predict document preferences in all cases; and (2) in the computation of most existing ranking metrics, not all document pairs are equally important. This means that the performance of pairwise preference prediction is not equal to the performance of the final retrieval results as a list. Given this problem, previous studies [95, 96, 97, 98] further proposed listwise ranking objectives for learning to rank.

5.1.3. Listwise Ranking Objective

The idea of listwise ranking objectives is to construct loss functions that directly reflect the model’s final performance in ranking. Instead of comparing two documents each time, listwise loss functions compute ranking loss with each query and their candidate document list together. Formally, most existing listwise loss functions can be formulated as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = \sum_i L(\{y_{i,j}, f(s_i, t_{i,j}) | t_{i,j} \in \mathcal{T}_i\}) \quad (8)$$

where \mathcal{T}_i is the set of candidate documents for query s_i . Usually, L is defined as a function over the list of documents sorted by $y_{i,j}$, which we refer to as π_i , and the list of documents sorted by $f(s_i, t_{i,j})$. For example, Xia et al. [95] proposed *ListMLE* for listwise ranking as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = \sum_i \sum_{j=1}^{|\pi_i|} \log P(y_{i,j} | \mathcal{T}_i^{(j)}, f) \quad (9)$$

560 where $P(y_{i,j}|\mathcal{T}_i^{(j)}, f)$ is the probability of selecting the j th document in the optimal ranked list π_i with f :

$$P(y_{i,j}|\mathcal{T}_i^{(j)}, f) = \frac{\exp(f(s_i, t_{i,j}))}{\sum_{k=j}^{|\pi_i|} \exp(f(s_i, t_{i,k}))} \quad (10)$$

Intuitively, ListMLE is the log likelihood of the optimal ranked list given the current ranking function f , but computing log likelihood on all the result positions is computationally prohibitive in practice. Thus, many alternative functions have been proposed for listwise ranking objectives in the past ten years. 565 One example is the *Attention Rank* function used in the Deep Listwise Context Model proposed by Ai et al. [98]:

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = - \sum_i \sum_j P(t_{i,j}|\mathcal{Y}_i, \mathcal{T}_i) \log P(t_{i,j}|f, \mathcal{T}_i)$$

where $P(t_{i,j}|\mathcal{Y}_i, \mathcal{T}_i) = \frac{\exp(y_{i,j})}{\sum_{k=1}^{|\mathcal{T}_i|} \exp(y_{i,k})}$, (11)

$$P(t_{i,j}|f, \mathcal{T}_i) = \frac{\exp(f(s_i, t_{i,j}))}{\sum_{k=1}^{|\mathcal{T}_i|} \exp(f(s_i, t_{i,k}))}$$

When the labels of documents (i.e., $y_{i,j}$) are binary, we can further simplify the Attention Rank function with a softmax cross entropy function as

$$L(f; \mathcal{S}, \mathcal{T}, \mathcal{Y}) = - \sum_i \sum_j y_{i,j} \log \frac{\exp(f(s_i, t_{i,j}))}{\sum_{k=1}^{|\mathcal{T}_i|} \exp(f(s_i, t_{i,k}))} \quad (12)$$

570 As far as we know, the softmax-based listwise ranking loss is one of the most popular learning objectives for neural ranking models, including DSSM [13], CDSSM [47], DUET [23], HEM [99], GSF [100], etc. It is particularly useful when we train neural ranking models with user behavior data (e.g., clicks) under the unbiased learning framework [101]. There are other types of listwise loss functions proposed under different ranking frameworks in the literature [97, 96]. 575 We ignore them in this paper since they are not popular in the studies of neural IR.

While listwise ranking objectives are generally more effective than pairwise ranking objectives, their high computational cost often limits their applications.

580 They are suitable for the re-ranking phase over a small set of candidate documents. Since many practical search systems now use neural models for document re-ranking, listwise ranking objectives have become increasingly popular in neural ranking frameworks [13, 47, 23, 98, 100, 101].

5.1.4. *Multi-task Learning Objective*

585 In some cases, the optimization of neural ranking models may include the learning of multiple ranking or non-ranking objectives at the same time. The motivation behind this approach is to use the information from one domain to help the understanding of information from other domains. For example, Liu et al. [102] proposed to unify the representation learning process for query classification and Web search by training a deep neural network in which the
590 final layer of hidden variables are used to optimize both a classification loss and a ranking loss. Chapelle et al. [103] proposed a multi-boost algorithm to simultaneously learn ranking functions based on search data collected from 15 countries.

595 In general, the most common methodology used by existing multi-task learning algorithms is to construct shared representations that are universally effective for ranking in multiple tasks or domains. To do so, previous studies mostly focus on constructing regularizations or restrictions on model optimizations so that the final model is not specifically designed for a single ranking objective [102, 103]. Inspired by recent advances on generative adversarial networks (GAN) [104], Cohen et al. [105] introduced an adversarial learning framework that jointly learns a ranking function with a discriminator which can distinguish data from different domains. By training the ranking function to produce representations that cannot be discriminated by the discriminator, they teach
600 the ranking system to capture domain-independent patterns that are usable in cross-domain applications. This is important as it can significantly alleviate the
605 problem of data sparsity in specific tasks and domains.

5.2. Training Strategies

Given the data available for training a neural ranking model, an appropriate
610 training strategy should be chosen. In this section, we briefly review a set
of effective training strategies for neural ranking models, including supervised,
semi-supervised, and weakly supervised learning.

Supervised learning refers to the most common learning strategy in which
query-document pairs are labeled. The data can be labeled by expert assess-
615 sors, crowdsourcing, or can be collected from the user interactions with a search
engine as implicit feedback. In this training strategy, it is assumed that a suffi-
cient amount of labeled training data is available. Given this training strategy,
one can train the model using any of the aforementioned learning objectives,
e.g., pointwise and pairwise. However, since neural ranking models are usually
620 data “hungry”, academic researchers can only learn models with constrained
parameter spaces under this training paradigm due to the limited annotated
data. This has motivated researchers to study learning from limited data for
information retrieval [106].

Weakly supervised learning refers to a learning strategy in which the query-
625 document labels are automatically generated using an existing retrieval model,
such as BM25. The use of pseudo-labels for training ranking models has been
proposed by Asadi et al. [107]. More recently, Dehghani et al. [27] proposed
to train neural ranking models using weak supervision and observed up to 35%
improvement compared to BM25 which plays the role of weak labeler. This
630 learning strategy does not require labeled training data. In addition to ranking,
weak supervision has shown successful results in other information retrieval
tasks, including query performance prediction [108], learning relevance-based
word embedding [109], and efficient learning to rank [110].

Semi-supervised learning refers to a learning strategy that leverages a small
635 set of labeled query-document pairs plus a large set of unlabeled data. Semi-
supervised learning has been extensively studied in the context of learning to
rank. Preference regularization [111], feature extraction using KernelPCA [112],
and pseudo-label generation using labeled data [113] are examples of such ap-

proaches. In the realm of neural models, fine-tuning weak supervision models
640 using a small set of labeled data [27] and controlling the learning rate in learning
from weakly supervised data using a small set of labeled data [114] are another
example of semi-supervised approaches to ranking. Recently, Li et al. [115]
proposed a neural model with a joint supervised and unsupervised loss func-
tions. The supervised loss accounts for the error in query-document matching,
645 while the unsupervised loss computes the document reconstruction error (i.e.,
auto-encoders).

6. Model Comparison

In this section, we compare the empirical evaluation results of the previously
reviewed neural ranking models on several popular benchmark data sets. We
650 mainly survey and analyze the published results of neural ranking models for
the ad-hoc retrieval and QA tasks. Note that sometimes it is difficult to com-
pare published results across different papers - small changes such as different
tokenization, stemming, etc. can lead to significant differences. Therefore, we
attempt to collect results from papers that contain comparisons across some of
655 these models performed at a single site for fairness .

6.1. Empirical Comparison on Ad-hoc Retrieval

To better understand the performances of different neural ranking models
on ad-hoc retrieval, we show the published experimental results on benchmark
datasets. Here, we choose three representative datasets for ad-hoc retrieval:
660 (1) Robust04 dataset is a standard ad-hoc retrieval dataset where the queries
are from TREC Robust Track 2004. (2) Gov2_{MQ2007} is an Web Track ad-hoc
retrieval dataset where the collection is the Gov2 corpus. The queries are from
the Million Query Track of TREC 2007. (3) Sougou-Log dataset [85] is built on
query logs sampled from search logs of Sougou.com. The detailed data statistics
665 can be found in related literature [21, 33, 34, 85].

Table 1 shows an overview of previous published results on ad-hoc retrieval
datasets. We have included some well-known probabilistic retrieval models,

Table 1: Overview of previously published results on ad hoc retrieval datasets. The citation in each row denotes the original paper where the method is proposed. The superscripts 1-5 denote that the results are cited from [21],[33],[34],[84], [28] respectively. The subscripts denote the model architecture belongs to (S)ymmetric or (A)symmetric/(R)epresentation-focused or (I)nteraction-focused or (H)ybrid/Singe-(G)ranularity or (Multi-granularity. The back slash symbols denote that there are no published results for the specific model on the specific data set in the related literature.

ModelData Set	Robust04		GOV2 _{MQ2007}		Sogou-Log	
	MAP	P@20	MAP	P@10	NDCG@1	NDCG@10
BM25[46] (1994) ^{2,4}	0.255	0.370	0.450	0.366	0.142	0.287
QL[116] (1998) ^{1,4}	0.253	0.369	\	\	0.126	0.282
RM3[117](2001) ⁴	0.287	0.377	\	\	\	\
RankSVM[118] (2002) ²	\	\	0.464	0.381	0.146	0.309
LambdaMart[97] (2010) ^{2,4}	\	\	0.468	0.384	\	\
DSSM[13] (2013) ^{1,2} _{S/R/G}	0.095	0.171	0.409	0.352	\	\
CDSSM[47] (2014) ^{1,2} _{S/R/G}	0.067	0.125	0.364	0.291	0.144	0.333
ARC-I[17] (2014) ^{1,2} _{S/R/G}	0.041	0.065	0.417	0.364	\	\
ARC-II[17] (2014) ^{1,2} _{S/I/G}	0.067	0.128	0.421	0.366	\	\
MP[18] (2016) ^{1,2} _{S/I/G}	0.189	0.290	0.434	0.371	0.218	0.380
Match-SRNN[69] (2016) ² _{S/H/G}	\	\	0.456	0.384	\	\
DRMM[21] (2016) ^{1,2,4} _{A/I/G}	0.279	0.382	0.467	0.388	0.137	0.315
Duet[23] (2017) ³ _{A/H/G}	\	\	0.474	0.398	\	\
DeepRank[33] (2017) ² _{A/I/G}	\	\	0.497	0.412	\	\
K-NRM[85] (2017) ⁴ _{A/I/G}	\	\	\	\	0.264	0.428
SNRM[28] (2018) ⁵ _{S/R/G}	0.286	0.377	\	\	\	\
SNRM+PRF[28] (2018) ⁵ _{S/R/G}	0.297	0.395	\	\	\	\
CONV-KNRM[84] (2018) ⁴ _{A/I/M}	\	\	\	\	0.336	0.481
HiNT[34] (2018) ³ _{A/I/G}	\	\	0.502	0.418	\	\

pseudo-relevance feedback (PRF) models and LTR models as baselines. Based on the results, we have the following observations:

- 670 1. The probabilistic models (i.e., QL and BM25), although simple, can already achieve reasonably good performance. The traditional PRF model (i.e., RM3) and LTR models (i.e., RankSVM and LambdaMart) with human designed features are strong baselines whose performance is hard to beat for most neural ranking models based on raw texts. However, the PRF technique can also be leveraged to enhance neural ranking models (e.g., SNRM+PRF [28] in Table 1), while human designed LTR features can be integrated into neural ranking models [33, 31] to improve the ranking performance.
- 675 2. There seems to be a paradigm shift of the neural ranking model architectures from symmetric to asymmetric and from representation-focused to interaction-focused over time. This is consistent with our previous analysis where asymmetric and interaction-focused structures may fit better with the ad-hoc retrieval task which shows heterogeneity inherently.
- 680 3. With bigger data size in terms of distinct number of queries and labels (i.e., Sogou-Log \succ GOV2_{MQ2007} \succ Robust04), neural models are more likely to achieve larger performance improvement against non-neural models. As we can see, the best neural models based on raw texts can significantly outperform LTR models with human designed features on GOV2_{MQ2007} and Sogou-Log.
- 685 4. Based on the reported results, in general, we observe that the asymmetric, interaction-focused, multi-granularity architecture can work better than the symmetric, representation-focused, single-granularity architecture on the ad-hoc retrieval tasks. There is one exception, i.e., SNRM on Robust04. However, this model was trained with a large amount of data using the weak supervision strategy, and may not be appropriate to directly compare with those models trained on Robust04 alone.
- 690
- 695

6.2. Empirical Comparison on QA

In order to understand the performance of different neural ranking models reviewed in this paper for the QA task, we survey the previously published results on three QA data sets, including TREC QA [119], WikiQA [37] and Yahoo! Answers [88]. TREC QA and WikiQA are answer sentence selection/retrieval data sets and they mainly contain factoid questions, while Yahoo! Answers is an answer passage retrieval data set sampled from the CQA website Yahoo! Answers. The detailed data statistics can be found in related literature [120, 37, 88]. The results on TREC QA are for the raw version¹⁰.

Table 2 shows the overview of the published results on the QA benchmark data sets. We include several traditional non-neural methods as baselines. We summarize our observations as follows:

1. Unlike ad-hoc retrieval, symmetric architectures have been more widely adopted in the QA tasks possibly due to the increased homogeneity between the question and the answer, especially for answer sentence retrieval data sets like TREC QA and WikiQA.
2. Representation-focused architectures have been more adopted on short answer sentence retrieval data sets, i.e., TREC QA and WikiQA, while interaction-focused architectures have been more adopted on longer answer passage retrieval data sets, e.g., Yahoo! Answer. However, unlike ad-hoc retrieval, there seems to be no clear winner between the representation-focused architecture and the interaction-focused architecture on QA tasks.
3. Similar to ad-hoc retrieval, neural models are more likely to achieve larger performance improvement against non-neural models on bigger data sets. For example, on small data set like TREC QA, feature engineering based methods such as LCLR can achieve very strong performance. However, on large data set like WikiQA and Yahoo! Answers, we can see a clear gap between neural models and non-neural models.

¹⁰[https://aclweb.org/aclwiki/Question_Answering_\(State_of_the_art\)](https://aclweb.org/aclwiki/Question_Answering_(State_of_the_art))

Table 2: Overview of previously published results on QA benchmark data sets. The citation in each row denotes the original paper where the method is proposed. The superscripts 1-10 denote that the results are cited from [37], [69], [61], [86], [88], [121], [87], [122], [120], [92] respectively. The subscripts denote the model architecture belongs to (S)ymmetric or (A)symmetric/(R)epresentation-focused or (I)nteraction-focused or (H)ybrid/Single-(G)ranularity or (M)ulti-granularity. The back slash symbols denote that there are no published results for the specific model on the specific data set in the related literature.

Data Set	TREC QA		WikiQA		Yahoo! Answers	
	MAP	MRR	MAP	MRR	P@1	MRR
BM25[46] (1994) ²	\	\	\	\	0.579	0.726
LCLR[123] (2013) ^{1,9}	0.709	0.770	0.599	0.609	\	\
Word Cnt[120] (2014) ^{1,9}	0.571	0.627	0.489	0.492	\	\
Wgt Word Cnt[120] (2014) ^{1,9}	0.596	0.652	0.510	0.513	\	\
DeepMatch[14] (2013) ⁵ _{S/I/G}	\	\	\	\	0.452	0.679
CNN[120] (2014) ^{1,9} _{S/R/G}	0.569	0.661	0.619	0.628	\	\
CNN-Cnt[120] (2014) ^{1,9} _{S/R/G}	0.711	0.785	0.652	0.665	\	\
ARC-I[17] (2014) ² _{S/R/G}	\	\	\	\	0.581	0.756
ARC-II[17] (2014) ² _{S/I/G}	\	\	\	\	0.591	0.765
CDNN[19] (2015) ³ _{S/R/G}	0.746	0.808	\	\	\	\
BLSTM[60] (2015) ³ _{S/R/G}	0.713	0.791	\	\	\	\
CNTN[25] (2015) ^{2,6} _{S/R/G}	0.728	0.783	\	\	0.626	0.781
MultiGranCNN[89] (2015) ² _{S/I/M}	\	\	\	\	0.725	0.840
LSTM-RNN[48] (2016) ² _{S/R/G}	\	\	\	\	0.690	0.822
MV-LSTM[88] (2016) ^{2,6} _{S/R/G}	0.708	0.782	\	\	0.766	0.869
MatchPyramid[18] (2016) ² _{S/I/G}	\	\	\	\	0.764	0.867
aNMM[61] (2016) ³ _{A/I/G}	0.750	0.811	\	\	\	\
Match-SRNN[69] (2016) ² _{S/I/G}	\	\	\	\	0.790	0.882
IARNN[86] (2016) ⁴ _{A/H/G}	\	\	0.734	0.742	\	\
HD-LSTM[121] (2017) ⁶ _{S/R/G}	0.750	0.815	\	\	\	\
CompAgg[87] (2017) ⁷ _{A/I/G}	\	\	0.743	0.755	\	\
HyperQA[122] (2018) ⁸ _{S/R/G}	0.770	0.825	0.712	0.727	\	\
MIX[92] (2018) ¹⁰ _{S/I/M}	\	\	0.713	\	\	\

725 4. The performance in general increases over time, which might be due to
the increased model capacity as well as the adoption of some advanced
approaches, e.g., the attention mechanism. For example, IARNN utilizes
attention-based RNN models with GRU to get an attentive sentence rep-
resentation. MIX extracts grammar information and integrates attention
730 matrices in the attention channels to encapsulate rich structural patterns.
aNMM adopts attention mechanism to encode question term importance
for aggregating interaction matching features.

7. Trending Topics

In this section, we discuss several trending topics related to neural ranking
735 models. Some of these topics are important but have not been well addressed
in this field, while some are very promising directions for future research.

7.1. Indexing: from Re-ranking to Ranking

Modern search engines take advantage of a multi-stage cascaded architecture
in order to efficiently provide accurate result lists to users. In more detail, there
740 can be a stack of rankers, starting from an efficient high-recall model. Learning
to rank models are often employed to model the last stage ranker whose goal is
to re-rank a small set of documents retrieved by the early stage rankers. The
main objective of these learning to rank models is to provide high-precision
results.

745 Such a multi-stage cascaded architecture suffers from an error propagation
problem. In other words, the errors initiated by the early stage rankers are
propagated to the last stage. This clearly shows that multi-stage systems are
not optimal. However, for efficiency reasons, learning to rank models cannot be
used as the sole ranker to retrieve from large collections, which is a disadvantage
750 for such models.

To address this issue, Zamani et al. [28] recently argued that the sparse
nature of natural languages enables efficient term-matching retrieval models to

take advantage of an *inverted index* data structure for efficient retrieval. Therefore, they proposed a standalone neural ranking model (SNRM) that learns
755 high-dimensional sparse representations for queries and documents. In more detail, this type of model should optimize two objectives: (i) a relevance objective that maximizes the effectiveness of the model in terms of the retrieval performance, and (ii) a sparsity objective that is equivalent to minimizing L_0 of the query and document representations. SNRM has shown superior performance compared to competitive baselines and has performed as efficiently as
760 term-matching models, such as TF-IDF and BM25.

Learning inverted indexes has been also started to be explored in the database community. Kraska et al. [124] recently proposed to look at indexes as models. For example, a B-Tree-Index can be seen as a function that maps each key to a
765 position of record in a sorted list. They proposed to replace traditional indexes used in databases with the indexes learned using deep learning technologies. Their models demonstrate a significant conflict reduction and memory footprint improvement.

Graph-based hashing and indexing algorithms have also attracted a considerable attention, which could be leveraged to index neural representations for
770 the initial retrieval. For instance, Boytsov et al. [125] proposed to replace term-matching retrieval models with approximate nearest neighbor algorithms. Van Gysel et al. [126] used a similar idea to design an unsupervised neural retrieval model, however, their model architecture is not scalable to large document collections.
775

Moving from re-ranking a small set of documents to retrieving documents from a large collection is a recent research direction with a number of unanswered questions that require further investigation. For example, understanding and interpreting the learned neural representations has yet to be addressed.
780 Furthermore, there is a known trade-off between efficiency and effectiveness in information retrieval systems, however, understanding this trade-off in learning inverted indexes requires further research. In addition, although index compression is a common technique in the search engine industry to reduce the size

of the posting lists and improve efficiency, compression of the learned latent
785 indexes is an unexplored area of research.

In summary, learning to index and developing effective and at the same time
efficient retrieval models is a promising direction in neural IR research, however,
we still face several open questions in this area.

7.2. *Learning with External Knowledge*

790 Most existing neural ranking models focus on learning the matching pat-
terns between the two input texts. In recent years, some researchers have gone
beyond matching textual objects by leveraging external knowledge to enhance
the ranking performance. These research works can be grouped into two cate-
gories: 1) learning with external structured knowledge such as knowledge bases
795 [127, 29, 128, 129, 130, 131]; 2) learning with external unstructured knowledge
such as retrieved top results, topics or tags [30, 132, 133]. We now briefly review
this work.

The first category of research explored improving neural ranking models
with semantic information from knowledge bases. Liu et al. [127] proposed
800 EDRM that incorporates entities in interaction-focused neural ranking mod-
els. EDRM first learns the distributed representations of entities using their
semantics from knowledge bases in descriptions and types. Then the model
matches documents to queries with both bag-of-words and bag-of-entities. Sim-
ilar approaches were proposed by Xiong et al. [29], which also models queries
805 and documents with word-based representations and entity-based representa-
tions. Nguyen et al. [128] proposed combining distributional semantics learned
through neural networks and symbolic semantics held by extracted concepts
or entities from text knowledge bases to enhance the learning algorithm of la-
tent representations of queries and documents. Shen et al. [129] proposed the
810 KABLSTM model, which leverages external knowledge from knowledge graphs
to enrich the representational learning of QA sentences. Xu et al. [131] designed
a Recall gate, where domain knowledge can be transformed into the extra global
memory of LSTM, with the aim of enhancing LSTM by cooperating with its lo-

cal memory to capture the implicit semantic relevance between sentences within
815 conversations.

Beyond structured knowledge in knowledge bases, other research has explored how to integrate external knowledge from unstructured texts, which are more common for information on the Web. Yang et al. [30] studied response ranking in information-seeking conversations and proposed two effective meth-
820 ods to incorporate external knowledge into neural ranking models with pseudo-relevance feedback (PRF) and QA correspondence knowledge distillation. They proposed to extract the “correspondence” regularities between question and answer terms from retrieved external QA pairs as external knowledge to help response selection. Another representative work on integrating unstructured
825 knowledge into neural ranking models is the KEHNN model proposed by Wu et al. [133], which defined prior knowledge as topics, tags, and entities related to the text pair. KEHNN represents global context obtained from external textual collection, and then exploits a knowledge gate to fuse the semantic information carried by the prior knowledge into the representation of words. Finally, it
830 generates a knowledge enhanced representation for each word to construct the interaction matrix between text pairs.

In summary, learning with external knowledge is an active research area related to neural ranking models. More research efforts are needed to improve the effectiveness of neural ranking models with distilled external knowledge and
835 to understand the role of external knowledge in ranking tasks.

7.3. Learning with Visualized Technology

We have discussed many neural ranking models in this survey under the textual IR scenario. There have also been a few studies showing that the textual IR problem could be solved visually. The key idea is that we can construct the
840 matching between two inputs as an image so that we can leverage deep neural models to estimate the relevance based on visual features. The advantage of the matching image, compared with traditional matching matrix, is that it can keep the layout information of the original inputs so that many useful features

such as spatial proximity, font size and colors could be modeled for relevance
845 estimation. This is especially useful when we consider ad-hoc retrieval tasks
on the Web where pages are often well designed documents with rich layout
information.

Specifically, Fan et al. [31] proposed a visual perception model (ViP) to per-
ceive visual features for relevance estimation. They first rendered the Web pages
850 into query-independent snapshots and query-dependent snapshots. Then, the
visual features are learned through a combination of CNN and LSTM, inspired
by users' reading behaviour. The results have demonstrated the effectiveness
of learning the visual features of document for ranking problems. Zhang et
al. [134] proposed a joint relevance estimation model which learns visual pat-
855 terns, textual semantics and presentation structures jointly from screenshots,
titles, snippets and HTML source codes of search results. Their results have
demonstrated the viability of the visual features in search result page relevance
estimation. Recently, visualized technology has also been directly applied to the
matching signals. For example, Tang et al. [32] proposed a DeepTileBars which
860 visualizes the relevance signals (i.e., word-to-word matching signals) through
the TileBars [135]. Then, a CNN is applied on the TileBar visualizations to
extract the relevance features.

In summary, solving the textual ranking problem through visualized technol-
ogy is a novel and interesting direction. In some sense, this approach simulates
865 human behavior as we also judge relevance through visual perception. The ex-
isting work has only demonstrated the effectiveness of visual features in some
relevance assessment tasks. However, more research is needed to understand
what can be learned by such visualized technology beyond those text-based
methods, and what IR applications could benefit from such models.

870 7.4. Learning with Context

Search queries are often short and cannot precisely express the underlying
information needs. To address this issue, a common strategy is to exploit *query*
context to improve the retrieval performance. Three types of query context have

been explored in the literature:

- 875 • Short-term history: the user past interactions with the system in the current search session [136, 137, 138].
- Long-term history: the historical information of the user’s queries that is often used for web search personalization [139, 140].
- 880 • Situational context: the properties of the current search request, independent from the query content, such as location and time [141, 142].

Although query context has been widely explored in the literature, incorporating query context into neural ranking models is relatively less studied. Zamani et al. [142] proposed a deep and wide network architecture in which the deep part of the model learns abstract representations for contextual features, while the wide part of the model uses raw contextual features in binary 885 format in order to avoid information loss as a result of high-level abstraction. Ahmad et al. [143] incorporated short-term history information into a neural ranking model by multi-task training of document ranking and query suggestion. Short- and long-term history have been also used by Chen et al. [144] for 890 query suggestion.

In summary, with the emergence of interactive or conversational search system, context-aware ranking would be an indispensable technology in these scenarios. These exist several open research questions on how to incorporate query context information in neural ranking models. More research work is expected 895 in this direction in the short future.

7.5. *Neural Ranking Model Understanding*

Deep learning techniques have been widely criticized as a “black box” which produces good results but no problem insights and explanations. Thus, how to understand and explain neural models has been an important topic in both 900 Machine Learning and IR communities. To the best of our knowledge, the explainability of neural ranking models has not been fully studied. Instead,

there have been a few papers on analyzing and understanding the empirical effect of different model components in IR tasks.

For example, Pang et al. [145] conducted an extensive analysis on the Match-
905 Pyramid model in ad-hoc retrieval and compared different kernels, pooling sizes, and similarity functions in terms of retrieval performance. Cohen et al. [146] extracted the internal representations of neural ranking models and evaluated their effectiveness in four natural language processing tasks. They find that topical relevance information is usually captured in the high-level layers of a neural
910 model. Nie et al. [147] conducted empirical studies on the interaction-based neural ranking model to understand what have been learned in each neural network layer. They also notice that low-level network layers tend to capture detailed text information while high-level layers tend to have higher topical information abstraction.

915 While the paradigms of analyzing neural ranking models often rely on a deep understanding of specific model structure, Cohen et al. [22] argue that there are some general patterns of which types of neural models are more suitable for each IR task. For example, retrieval tasks with fine granularity (e.g., factoid QA) usually need higher levels of information abstraction and semantic matching,
920 while retrieval tasks with coarse granularity (e.g., document retrieval) often rely on the exact matching or interaction between query words and document words.

Overall, the research area on the explainability of neural ranking models is largely unexplored up till now. Some skepticism about neural ranking models
925 is also related to this, e.g., what new things can be learned by neural ranking models? It is a very challenging and promising direction for researchers in neural IR.

8. Conclusion

The purpose of this survey is to summarize the current research status on
930 neural ranking models, analyze the existing methodologies, and gain some in-

sights for future development. We introduced a unified formulation over the neural ranking models, and reviewed existing models based on this formulation from different dimensions under model architecture and model learning. For model architecture analysis, we reviewed existing models to understand their
935 underlying assumptions and major design principles, including how to treat the inputs, how to consider the relevance features, and how to make evaluation. For model learning analysis, we reviewed popular learning objectives and training strategies adopted for neural ranking models. To better understand the current status of neural ranking models on major applications, we surveyed published
940 empirical results on the ad-hoc retrieval and QA tasks to conduct a comprehensive comparison. In addition, we discussed several trending topics that are important or might be promising in the future.

Just as there has been an explosion in the development of many deep learning based methods, research on neural ranking models has increased rapidly and
945 broadened in terms of applications. We hope this survey can help researchers who are interested in this direction, and will motivate new ideas by looking at past successes and failures. Neural ranking models are part of the broader research field of neural IR, which is a joint domain of deep learning and IR technologies with many opportunities for new research and applications. We are
950 expecting that, through the efforts of the community, significant breakthroughs will be achieved in this domain in the near future, similar to those happened in computer vision or NLP.

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