Optimizing Relational Search With Embedded Neural Network

by

Limin Ma

A thesis submitted to the
School of Graduate and Postdoctoral Studies in partial
fulfillment of the requirements for the degree of

Master of Science in Computer Science

Faculty of Science

University of Ontario Institute of Technology (Ontario Tech University)

Oshawa, Ontario, Canada

April 2023

THESIS EXAMINATION INFORMATION

Submitted by: **Limin Ma**

Master of Science in **Computer Science**

Thesis title: Optimizing Relational Search With Embedded Neural Network

An oral defense of this thesis took place on March 29, 2023 in front of the following examining committee:

Examining Committee:

Chair of Examining Committee	Dr. Ying Zhu
Research Supervisor	Dr. Ken Pu
Examining Committee Member	Dr. Heidar Davoudi
Thesis Examiner	Dr. Steven Livingstone

The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

Abstract

Our research focuses on a novel method to query relational data. We propose the partial tuple search problem where a user can utilize keyword search to explore complex relational datasets. The challenge of evaluation of partial tuple queries is the performance bottleneck of fuzzy string matching using traditional full-text index structures. We propose a solution to overcome the bottleneck by incorporating horizontally partitioned full-text indexes and an embeddable neural network classifier in the query processing pipeline. The classifier is trained with self-supervision. It learns to optimize the partitioned indexes access pattern to accelerate query performance. Using textual features of user queries, the classifier infers the index access pattern so that fuzzy string matching subqueries are efficiently evaluated. We studied various network architectures and evaluated them against real-world datasets. Our experimental evaluation demonstrates that neural networks successfully learned how to optimize index access patterns for this use case.

Keywords: neural network; relational database; keyword search; optimization

Author's Declaration

Limin Ma

Statement of Contributions

Part of the work described in Chapter 3 has been published as:

L. Ma and K. Q. Pu, "Neural Network Accelerated Tuple Search For Relational Data," 2022 IEEE 23rd International Conference on Information Reuse and Integration for Data Science (IRI), San Diego, CA, USA, 2022, pp. 81-82, doi: 10.1109/IRI54793.2022.00029.

I performed the majority of design, implementation, experimental evaluation and preparation of the manuscript.

Acknowledgements

I would like to express my utmost gratitude to my supervisor, Dr. Ken Pu, for his guidance, encouragement and support. I would also like to thank my committee members, Dr. Heidar Davoudi and Dr. Steven Livingstone. I am grateful for their valuable feedback on this thesis. Last but not least, I am thankful to my wife Xiao Wang and the rest of my family. All have provided me with patience and support for the challenges I faced in order to perform research and write this thesis. None of this would have been possible without their support.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation

For many decades, with the availability of low cost computers and Internet access, the amount of digital information or data has increased at an ever growing pace. This poses a challenge to managing information reliably and efficiently.

Various database technologies and query processing engines have been developed over the past several decades to meet the appetite of information management. There are two main types of databases, relational database and non-relational database. Relational database management system (RDBMS) is a pillar of database technology. MySQL and PostgreSQL are two examples of open source RDBMS. Examples of non-relational databases include semi-structured databases such as MongoDB [**mongodb**] and graph databases such as Neo4j [**neo4j**].

In contrast to its peers, RDBMS is proven to be the preferred choice for most of the data management needs. There are several reasons:

- Relational databases help businesses' utilization of data by maintaining data in a simple and efficient way. The relational data model is simple, easy to use and type-safe. Relational databases are typically capable of handling transactions, which is often required by businesses. The schema management features of RDBMS are robust enough to accurately model business and application requirements, and yet at the same time, provide a rich set of constraints and data consistency checks. Thus, RDBMS provides a higher level of data consistency.

- The Structured Query Language (SQL) is the standard programming language for managing data in relational databases. SQL has been the de facto industry standard for data analysis for several decades, and is still the most widely used method. It can quickly and efficiently process queries with the help of highly optimized SQL engines. It does not require extensive coding and programming skills, and offers users an interactive interface with underlying databases.
- Storing data using relational format is the safest choice when facing with the risks of digital data decay and software incompatibility issues. RDBMSes are widely used in various applications including mobile apps, Web services, distributed computing clusters, etc. because they offer robust data management capabilities. Combined with SQL's portability, RDBMS and SQL provide the most readily available software compatibility.

The dominance of RDBMS started to be challenged by the rise of the World Wide Web. The default mode of content creation on the World Wide Web is textual data and unstructured data. Such content apparently lacks relational structures. Therefore, it is unnatural to fit such data into RDBMS systems. Consequently, SQL is no longer the most suitable language to express queries over textual and unstructured data.

The need to carry out web searches gave the birth of search engines. Search engines started to popularize key-value stores as a preferred choice of data storage, and keyword search as a preferred choice for data retrieval. As modern search engines demonstrated, keyword search is a surprisingly effective approach of data retrieval. Furthermore, highly scalable and performant full-text indexes, such as Apache Lucene, are available to support keyword search queries at scale. But at the same time, keyword search has limitations that can not be ignored. Primarily, keyword search does not offer ways to reason over a data schema, and thus does not offer the end users ways to easily provide relational joins, selection over predicates or data analytics.

In attempts to overcome the limitations of keyword search while preserving its advantages, many researchers have proposed hybrid query languages that share features of SQL and keyword search. Most of the proposed systems extend SQL with keyword search, and use a relational database as data storage. While such systems do address the limitations of both SQL and keyword search over relational data to some extent, a common issue is scalability. The performance bottleneck is the inefficiency of relational database indexes when used for full-text search.

In this thesis, we are motivated by the following questions:

- Can we extend keyword search queries to enhance their expressive power when the underlying data is relational?

- Can we utilize full-text indexes that are designed for keyword search to answer searching of relational data?

- What are different ways to optimize the evaluation of keyword search queries?

1.2 Machine Learning

The rise of machine learning in recent years was due to two major factors, the explosion of data and the ever more affordable computing power. The ubiquitousness of Internet created the explosion of data that machine learning can consume, and cheap computing resources made it possible to train machine learning algorithms using large amounts of data. Machine learning has found successful applications in almost every corner of computer science and engineering. The most prominent tool in machine learning is neural networks. Complex neural network architectures have been designed and trained to perform various tasks at near-human or superhuman levels. One example is AlphaGo, which is a computer program that plays the board game Go. It grabbed the world's attention by defeating a Go world champion in 2016 [**alphago**].

What is particularly amazing about machine learning's success is how widely neural network approaches can be applied, ranging from images to texts, from semantic understanding to content generation.

The best aspects of applying neural networks as part (or whole) of a solution are:

- Neural networks are more robust than deterministic and combinatorial algorithms. Given when the input to the network deviates from expectation, the network can complete the processing in a continuous fashion, often producing near optimal results.

- Neural networks can be much faster during inference mode. Since neural networks essentially involve only matrix based numerical operations, they are well suited for modern CPUs and general purpose GPUs. In contrast, traditional algorithms utilize more complex data structures which often require large amounts of random memory access, making them difficult to optimize at the CPU / GPU level.

- Neural networks are easier at design time. Machine learning approaches shift the solution complexity from algorithmic design to data collection. When designing a neural network, we are essentially choosing the right black box that fits the overall system the best. The challenge is not to design the internal parameters of the black box, but rather to gather sufficient data to evaluate the quality of different candidate blackboxes. It's been repeatedly demonstrated in the domains including but not limited to image processing, natural language processing and combinatorial games, neural networks with simple architectures (but large number of parameters) outperform sophisticated handcrafted algorithms.

Traditionally, network based approaches require the availability of a large corpora of training data. Often this requires either expensive data collection schemes or human manual labeling of data. But in situations where training data is not available, it is still possible to apply neural networks. Self-supervised learning and reinforcement learning are just two examples of training neural networks without prior labeled training data.

While our research objective is novel keyword queries of relational databases, we are particularly motivated to incorporate neural networks into our query processing pipeline in a self-supervised manner. Towards this goal, we will need to

- identify problems that can be solved using self-supervised neural networks.
- design neural networks and incorporate them into the query processing pipeline.

1.3 Overview of thesis

The problems we address in this thesis are:

- extension of keyword search queries over relational data in ways that we can still enjoy efficient query evaluation using full-text indexes.
- identify components in the query evaluation pipeline that can be optimized by self-supervised neural networks.

Towards the first problem, we proposed a novel relational search problem we call *partial tuple search*. It is a generalization of keyword search by allowing users to specify *partial tuples* as queries, which can have both value-based keywords and schema-based structure information. Partial tuples can be used for information retrieval when users have limited, but nonzero, knowledge over the schema of the underlying relational database.

We demonstrate that a partial tuple search query can be evaluated in a pipeline consisting of the following stages:

- Generating a keyword query from a partial tuple.
- Evaluating the keyword query using one or more full-text indexes.
- Completing the partial tuple by matching keyword search results with the partial tuple.

It is well known that fuzzy string matching is generally more expensive to evaluate keyword search queries. In our use case, when we perform fuzzy partial tuple search, the full-text index becomes the performance bottleneck. A solution is to partition the full-text index, and perform fuzzy keyword search over multiple partitions. This creates a query optimization opportunity: a well selected index access pattern can speed up the keyword search performance without the additional burden of parallel CPU load.

We have designed neural networks that can learn from the relational data to optimize index access patterns. The neural network performs classification based on features from textual data in the relational database. Using the classification probability we can optimize index access patterns so that search time is minimized.

Chapter 2

Background

2.1 Relational Data Model

We describe the relational data model in this section. It is the foundation of the search problem that is studied in this thesis.

Let R be a relation and $\text{attr}(R)$ be the attributes of R. The attributes are a set of names. Each tuple of R is a function that maps attributes of R to values:

$$t : \text{attr}(R) \to \textbf{Values}$$

The relation R is a set of such tuples:

$$R = \{t_1, t_2, \ldots, t_n\}$$

Example 1. Consider a table shown below:

Name	**Address**
Jack	100 Simcoe Street
Jill	56 Taunton Road
Joe	5 Collin Road

The attributes are:

$$\text{attr}(R) = \{\text{Name}, \text{Address}\}$$

The relation consists of three tuples:

$$R = \{t_1, t_2, t_3\}$$

where t_1 is a mapping given by:

$$t_1 = \begin{bmatrix} \text{Name} & \mapsto & \text{Jack} \\ \text{Address} & \mapsto & \text{100 Simcoe Street} \end{bmatrix}$$

The other two tuples, t_2 and t_3, are defined similarly.

A relational database will have more features added to its relational model. For example,

- Primary keys and foreign keys
- Dependencies and constraints
- Structured query language (SQL)

More details can be found in texts such as García-Molina et al [**garcia2005database**]. However, in the context of our thesis, we do not rely on these additional features of a relational model. More precisely, the relational model we focus on is the first normal form [**beeri1979computational**].

2.2 Document Models

While the relational model is widely used, it does have limitations. One such limitation is the lack of flexibility of its schema, namely, all tuples of the same relation *must* have the same set of attributes.

Text search engines popularized the document model [**croft2010search**]. It supports schema-less data management. In the document model, a document is defined as a mapping from *fields* to text values.

2.2.1 Documents

Let d be a document and $\mathrm{attr}(d)$ be its set of fields. The fields $\mathrm{attr}(d)$ is a set of names, similar to the attributes of a relation. The document d is a function that maps fields to text:

$$d : \mathrm{attr}(d) \to \mathbf{Text}$$

A document collection is denoted by $D = \{d_1, d_2, \ldots, d_n\}$. It's important to note that a document collection is fundamentally different from a relation, that is,

different documents d, d' $(d \neq d')$ can have different fields: $\mathrm{attr}(d) \neq \mathrm{attr}(d')$.

Example 2. Consider three documents in a document collection D. The first has two fields: *Name* and *Address*. It can be denoted as:

$$d_1 = \begin{bmatrix} \text{Name} & \mapsto & \text{Jack} \\ \text{Address} & \mapsto & \text{100 Simcoe Street} \end{bmatrix}$$

The second has three fields: *Name*, *Occupation*, and *Address*. It can be denoted as:

$$d_2 = \begin{bmatrix} \text{Name} & \mapsto & \text{Jack} \\ \text{Occupation} & \mapsto & \text{Student} \\ \text{Address} & \mapsto & \text{100 Simcoe Street} \end{bmatrix}$$

The third has four fields: *Restaurant Name*, *City*, *Rating*, and *Comment*. It can be denoted as:

$$d_3 = \begin{bmatrix} \text{RestaurantName} & \mapsto & \text{The Best Grill} \\ \text{City} & \mapsto & \text{Oshawa} \\ \text{Rating} & \mapsto & 5 \\ \text{Comment} & \mapsto & \text{very nice place} \end{bmatrix}$$

2.2.2 Tokenization

The main objective of the document model is to support keyword search efficiently. This involves searching for documents whose fields contain certain sub-strings, which we call *tokens*. The process of token generation is referred to as tokenization (also known as lexical analysis). Tokenization is an important step in natural language processing [**jimenez2018impact**, **kudo2018sentencepiece**], especially for non-English languages [**takaoka2018sudachi**, **cao2011research**].

Before we can store the documents, we first need to transform text values into lists of tokens. We do this by using a tokenizer:

$$\textbf{tokenize} : \textbf{Text} \to \textbf{List}[\textbf{Token}]$$

Given a document d, a *term* is a field-token pair that is derived from the result of tokenzing the text value of a field. Then the term set of a document d is given by:

$$\mathbf{termset}(d) = \{(f, x) : f \in \mathrm{attr}(d),\ x \in \mathbf{tokenize}(d(f))\}$$

Given a document collection D, a simple document query is to find all documents with a specific term: $term^* = (f^*, x^*)$. The answer set to the query is given as:

$$\mathbf{answerset}(D, term^*) = \{d \in D : term^* \in \mathbf{termset}(d)\}$$

Example 3. Consider the above three documents in the document collection D of Example **??**. If we search field "Address" by keyword "Simcoe", the search query is:

$$term^* = (Address, Simcoe)$$

. The answer set will be:

$$\mathbf{answerset}(D, term^*) = \{d1, d2\}$$

2.2.3 Keyword queries and matching scores

Internet search engines made keyword queries as a standard way of accessing text documents [**ntoulas2004s**]. Important aspects of keyword queries are:

- There is no fixed syntax: queries can be as simple as a phrase or a piece of plain text.
- The search results do not need to match the query perfectly. They are ranked by some matching scores instead.

A *keyword query* is a text, annotated by a field name.

$$Q = (f_q, q)$$

where f_q is a field name, and $q \in \mathbf{Text}$.

The matching between the query $Q = (f_q, q)$ and the documents in a collection D is determined by the matching of their respective termsets. The termset of the query is defined as:

$$\mathbf{termset}(Q) = \{(f_q, x) : x \in \mathbf{tokenize}(q)\}$$

A natural matching score between Q and some document d is the overlap between their termsets. The Jaccard similarity measures a normalized overlap as defined as:

$$\mathrm{sim}(Q, d) = \frac{|\mathbf{termset}(Q) \cap \mathbf{termset}(d)|}{|\mathbf{termset}(Q) \cup \mathbf{termset}(d)|}$$

Jaccard similarity is sufficient in many document retrieval scenarios. However, it is not the ideal measure for documents based on natural languages. There are many words in the vocabulary of natural language text that have overwhelming high frequencies, for example, *the*, *a*, *this*, etc. Their occurrences should be discounted towards the similarity score. *Term frequency-inverse document frequency* (tf-idf) measure is a term-normalized score better suited for natural language based query-document matching.

Each term $t \in \mathbf{termset}(d)$ in a document d has a weight, known as its tf-idf weight, defined as follows.

Denote the number of occurrences of t in d as $\#(t, d)$. The term frequency is the normalized number of occurrences of t:

$$\mathrm{TF}(t,d) = \frac{\#(t,d)}{\sum_{x \in \mathbf{termset}(d)} \#(x,d)}$$

In order to discount frequent words, we also compute the *inverse document frequency* of t with respect to the entire document collection D:

$$\mathrm{IDF(t)} = \log \frac{|D|}{|\{d \in D : t \in \mathbf{termset}(d)\}|}$$

Note that $\mathrm{IDF}(t)$ is inversely proportional to the popularity of a word. Frequently occurring words have lower IDF weights.

Finally, the TF-IDF weight is the produce:

$$\mathbf{TFIDF}(t,d) = \mathrm{TF}(t,d) \cdot \mathrm{IDF}(t)$$

If a term t does not appear in a document d, then its TF-IDF weight is zero. Each document and query can be seen as a (sparse) vector of TF-IDF weights, and their matching score is measured by the cosine similarity of their TF-IDF vector representation.

$$\mathrm{sim}(Q,d) = \frac{\sum_x \mathbf{TFIDF}(x,Q)\mathbf{TFIDF}(x,d)}{\sqrt{\sum_x \mathbf{TFIDF}(x,Q)^2 \sum_y \mathbf{TFIDF}(y,d)^2}} \tag{2.1}$$

Equation **??** provides an unbiased measure of similarity between the termsets of the query and a document by discounting frequently occurring words.

2.3 Document Indexes and Search Engines

In the previous section, we have defined a number of similarity measures which can be used to rank *all* documents with respect to a user defined query.

A search engine needs to efficiently identify the top-k matching documents using some similarity score. A naive approach would require evaluating the similarity score of all the documents, which has a data complexity of $\mathcal{O}(n)$, where n is the total number of documents. For large document corpora, search engines need better algorithms for keyword query processing.

The most widely used data structure for keyword search is the *inverted term index.* Let D be a document collection. The term set of D is given by,

$$\mathbf{termset}(D) = \{\mathbf{termset}(d) : d \in D\}$$

Let $\mathbf{id}(d)$ be the id of a document d. The inverted term index is a function mapping terms to lists of document ids,

$$\mathbf{index} : \mathbf{termset}(D) \rightarrow \mathbf{List}[\mathbf{id}(d) : d \in D]$$

Example 4. Consider the three examples in Example **??**. The inverted term index can be denoted as,

$$\begin{bmatrix} \text{(Name, Jack)} & \mapsto & \{\text{d1, d2}\} \\ \text{(Address, 100)} & \mapsto & \{\text{d1, d2}\} \\ \text{(Address, Simcoe)} & \mapsto & \{\text{d1, d2}\} \\ \text{(Address, Street)} & \mapsto & \{\text{d1, d2}\} \\ \text{(Occupation, Student)} & \mapsto & \{\text{d2}\} \\ \text{(RestaurantName, The)} & \mapsto & \{\text{d3 }\} \\ \text{(RestaurantName, Best)} & \mapsto & \{\text{d3 }\} \\ \text{(RestaurantName, Grill)} & \mapsto & \{\text{d3 }\} \\ \text{(City, Oshawa)} & \mapsto & \{\text{d3}\} \\ \text{(Rating, 5)} & \mapsto & \{\text{d3}\} \\ \text{(Comment, very)} & \mapsto & \{\text{d3}\} \\ \text{(Comment, nice)} & \mapsto & \{\text{d3}\} \\ \text{(Comment, place)} & \mapsto & \{\text{d3}\} \end{bmatrix}$$

2.3.1 Keyword query performance

Inverted term index [**putz1991using**], as illustrated in Figure **??**, has two main components: a dictionary and lists of document ids. We use the dictionary to look up a search term. After that, we retrieve the list of document ids associated with the term. Therefore, the query performance is determined by looking up terms of the query in the dictionary and merging all matched document id lists.

Let $q =< t_1, t_2, \ldots, t_k >$ be a query, where t_i are terms and k is the number of terms of the query. The average length of document id lists is denoted as l. The total number of terms in the inverted index is denoted as N. Looking up a term t_i has $\mathcal{O}(\log N)$ complexity. Merging matched document lists requires linear scan, which

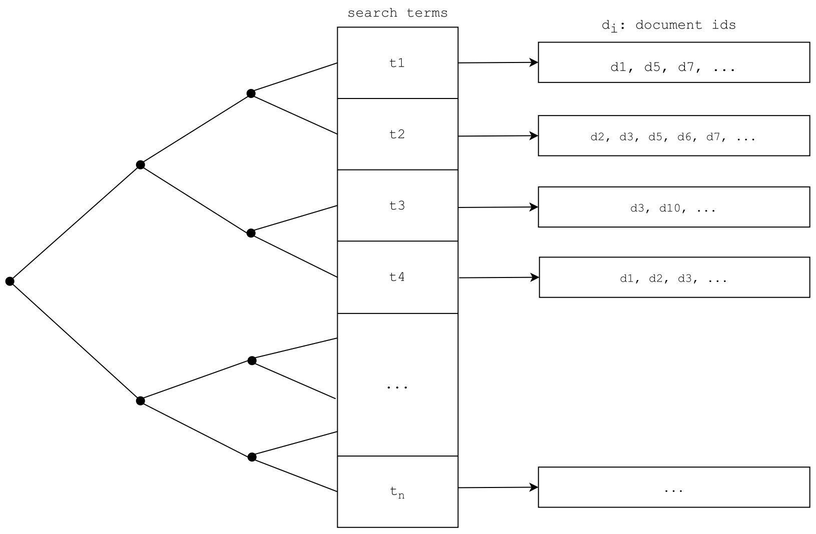


Figure 2.1: Inverted Term Index

has $\mathcal{O}(k \times l)$ complexity . Therefore, the time complexity of processing the query is $\mathcal{O}(k \times \log N) + \mathcal{O}(k \times l)$.

2.3.2 Fuzzy string matching and collisions

A particularly important feature of keyword search based information retrieval is *fuzzy string matching.* A common practice in performing fuzzy string matching based on the *n-grams* of the text [**kim1994fast**].

Definition 1 (n-grams)**.** *Let s be a string where $s(i)$ is the i-th character from some alphabet Σ. Let $n \geq 1$ be an integer. The n-padded string of s is obtained by prepending and appending $n-1$ special symbols to s, defined as:*

$$s' = \underbrace{'\$' \ldots '\$'}_{n-1 \text{ times}} \cdot s \cdot \underbrace{'\$' \ldots '\$'}_{n-1 \text{ times}}$$

The n-gram of s is the set of strings of length n defined as:

$$\mathrm{G}_n(s) = \{s'(i) \ldots s'(i+n-1) : 1 \leq i \leq |s'| - n + 1\}$$

By definition, $G_n(s) \subseteq (\Sigma \cup \{\$\})^n$, namely all of its segments of length n including the padded special character \$.

Example 5. Suppose that $s =$ "`computer`". Its 3-grams are given as:

$$G_3(s) = \{\texttt{\$\$c}, \texttt{\$co}, \texttt{com}, \texttt{omp}, \texttt{mpu}, \texttt{put}, \texttt{ute}, \texttt{ter}, \texttt{er\$}, \texttt{r\$\$}\}$$

Since $G_n(s)$ is a set that is derived from the content of s, we can use it as a feature to compare strings in an approximate way.

Definition 2 (Jaccard Similarity)**.** *Given two sets A and B, their Jaccard similarity is given by:*

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

Note $0 \leq J(A, B) \leq 1$*, with* $J(A, B) = 1$ *if and only if* $A = B$*.*

Using Jaccard similarity (and its derivatives), we can introduce a similarity measure over strings. Given two strings s_1 and s_2, the Jaccard similarity of the two strings is given by:

$$J(s_1, s_2) = J(G_n(s_1), G_n(s_2))$$

Now we can perform fuzzy string search using Jaccard similarity over strings. We index documents by storing their n-gram sets. The inverted index, therefore, will have n-gram tokens. We also break all queries into n-gram sets for searching. Commonly 3-grams yield the best trade-off for the English language.

Recall that the inverted term index maps tokens to documents. When 3-gram tokens are used, the total possible number of distinct tokens are given by $|\Sigma|^3$. For the English language, $|\Sigma| \simeq 50$ (based on ASCII encoding). So, there will only be $50^3 = 125,000$ possible tokens. But, at the same time, a typical text index needs to support up to billions of documents. As the number of documents exceeds the number of possible tokens, we run into the bad situation of severe collisions, which degrades the performance from log-time $\mathcal{O}(\log n)$ to sequential scan $\mathcal{O}(n)$.

In this thesis, we will encounter the bottleneck of collision when 3-grams are used as tokens. We will study methods involving partitioning the index, and optimizing index access pattern so that the search speed is improved. Our optimization method will involve neural networks to learn the optimal access patterns using self-supervised learning.

In subsequent sections, we will review some elements of neural network design that are necessary to construct our embedded networks.

2.4 Learning with neural networks

A neural network allows us to find patterns based on its training data. A trained neural network is an approximation of a function that maps its input data to its output data. In the context of this thesis, we explore ways to design neural networks as classifiers that will map partial tuple search queries to the relations that contain the tuples.

2.4.1 General framework of machine learning

The general framework of machine learning consists of three main components: representation of training data, a trainable model, and an optimization algorithm [**lecun2015deep**,

bengio2017deep].

There are different types of data that can be used for machine learning, such as numerical data, text documents, images, and so on. They have to be converted to some format before they can be consumed by a machine learning model. In natural language processing, we use embedding vectors, which are numerical vectors, to represent texts [**li2018word**, **tripathy2021comprehensive**].

Fundamentally, the problem that machine learning (ML) is addressing must be modeled as a function:

$$f : X \to Y$$

where X is a vector space that is the encoding of the input objects, and Y is the output (usually also a vector space). In the context of machine learning, the exact form of f, either mathematically or computationally, is not available. However, we assume that we have many observations of the input-output pairs $\{(x_i, y_i) : i = 1 \ldots n\}$ of f. The collection of (x, y) pairs is known as the *training data*.

A trainable model is an algorithm that can learn from the training data. In the case of a neural network model, we define its structure by layers. We specify the number of layers the model consists of, the layer types, the number of neurons in each layer, and the connections between layers. The network structure determines the capabilities of the model.

We highlight the following layer architectures that are used in this thesis.

- Embedding layer: this layer architecture converts discrete and categorical inputs to dense vectors using a *hard coded* lookup table that maps tokens from a vocabulary to embedding vectors. We will discuss this in more detail in Section **??**. The parameters of the embedding layer store the lookup table.

- Linear layer: this is the layer that is capable of performing linear separation in high dimensional space. A linear layer is most commonly used as a hidden layer or an output layer to produce the intermediate or final logits for a multi-class classification problem. It has a dense connection between the input and output. Generally, its dense connection makes it unsuitable to capture spatial and sparsely distributed features in the input. The parameters of the linear layer store the matrix and bias used in the linear transformation.

- Convolution layer: this layer architecture is designed to address the dense connection problem of the linear layer. Using the mathematical operation known as *convolution*, the convolution layer has spare connections between its input and output, and thus can learn localized features in the input. The parameters of the convolution layer store the *kernels* used in the convolution.

- Recurrent layer: the recurrent layer processes sequential inputs, namely it maintains an internal high dimensional state so that its output sequence depends (indirectly) on all previous inputs. The parameters of the recurrent layer store the matrices (and bias) used to update the internal state, and generate the sequential output.

- Attention layer: the attention layer is motivated by the inter-input dependencies. It performs transformation on two sets of input vectors by finding dependencies between vectors in one set and those in the other set. In the case of self-attention, the same set of vectors are used as both sets. The parameters of the attention layer store the transformation matrices that combine the two sets of input vectors.

A complete model consists of compositions of different layers by connecting the output of one or more layers to the input of downstream layers. A final output layer produces the output of the model. The parameters of the model are the collection of the parameters of all layers.

An optimization algorithm is the working force to tune the model. We define an objective function and use the optimization algorithm to minimize or maximize it. One typical example of an objective function is a loss function. It computes the error between the prediction and the target. Therefore, the goal of model training is to minimize the error. Various optimization algorithms exist, such as gradient descent, least square error minimization, etc. For neural network model training, we can use gradient descent to iteratively update the network weights to minimize the loss.

Once the model is trained, we can use it for prediction. A neural network model will process input data through its layers and produce an output, which is the prediction of the model. The quality of the prediction will depend on the quality of the training data, the model's architecture, and the effectiveness of the training process.

In the following sections, we describe embedding layer and specific neural network architectures that we use in our research.

2.4.2 Embedding layer

Embeddings are vectors of floating point numbers that can be used to represent various types of data, such as text, images, audio, etc. In a natural language processing (NLP) system, the embedding layer is a crucial component. It converts words into numerical vectors with fixed dimensions, which are dense representations of texts.

The main advantage of using embedding layers is that they can capture the complex relationships and semantic meanings of words within a language. Traditional NLP techniques often rely on one-hot encoding, where each word is represented by a binary vector with a “1” in the position corresponding to the word and “0”s in all other positions. This approach does not account for the semantic or syntactic relationships between words.

In contrast, embedding layers use a continuous vector space where words with similar meanings are clustered together. This allows the NLP model to better understand the context and meaning of words in a sentence, improving its performance on tasks such as sentiment analysis or language translation. Additionally, because embedding layers have fewer dimensions than one-hot encoded vectors, they require less computational resources and can be trained more efficiently.

Let $\mathbf{Voc}$ be a set of categorical values. Each element $t \in \mathbf{Voc}$ is called a token. Without loss of generality, we arbitrarily sort the vocabulary, and thus we can assume $\mathbf{Voc} = \{1, 2, \ldots, N\}$ where $N = |\mathbf{Voc}|$. Thus, we can assume that each token is a natural number in $[1, N]$.

The embedding layer has a trainable parameter: $E \in \mathbb{R}^{N\times k}$ for some $k > 0$. It maps each possible token t to a k-dimensional vector: $E[t] \in \mathbb{R}^k$, which is known as the *embedding vector* of the token t.

Since all other layers assume vectors as inputs, the embedding layer is almost always used as the input layer to a neural network that processes discrete values.

2.4.3 Multilayer perceptrons

A Multilayer Perceptron (MLP) is a type of neural network with a simple, feedforward architecture. It consists of an input layer, one or more hidden layers, and an output layer. The input layer receives the input data, and each subsequent layer receives the output of the previous layer as input. The output of the final layer is the network’s prediction.

MLPs are simple and easy to train, making them a popular choice for many applications. They are also versatile, as they can be used for a wide variety of tasks, including classification, regression, and clustering. Additionally, MLPs are able to learn non-linear relationships, which is not possible with simpler models such as linear regression. This makes them well-suited for many real-world problems where the relationship between the input and output is not strictly linear.

The MLP consists of two linear layers: a hidden layer and an output layer.

$$\begin{aligned} f_1 &: \mathbb{R}^m \to \mathbb{R}^h : x \mapsto \sigma_1(W_1 x + b_1) \\ f_2 &: \mathbb{R}^h \to \mathbb{R}^n : x \mapsto \sigma_2(W_2 x + b_2) \end{aligned}$$

where (W_i, b_i) is the transformation matrix and bias vector of layer i, and σ_i is a non-linear activation function.

MLP is the composition of the two layers:

$$\mathbf{MLP}(x) = f2(f1(x))$$

MLPs can be applied to Natural Language Processing (NLP) applications in several ways. One common approach is to use an MLP to classify text documents or sentences according to their content. For example, an MLP could be trained to classify a sentence as positive or negative sentiment, or to categorize it into one of several predefined categories such as sports, politics, or entertainment.

Another way in which MLPs can be used in NLP is for language translation. In this case, the MLP would be trained on a large dataset of sentence pairs in different languages, with the goal of learning to translate a sentence in one language to the corresponding sentence in the other language. The input to the network would be a sentence in the source language, and the output would be the translation in the target language.

2.4.4 Sequence learning with recurrent neural networks

Sequence learning is a type of machine learning that trains models to make predictions based on sequential data, such as time series data or natural language texts. Recurrent neural networks (RNNs) are a type of neural network that is very capable of handling sequence learning tasks. This is because they are able to retain information from previous time steps and use it to inform their prediction of the next time step. This allows RNNs to make predictions about data that has dependencies on previous data points, such as the next value in a time series or the next word in a sentence of natural language.

The input of a RNN is a sequence of vectors from $(\mathbb{R}^m)^*$. An RNN has two inner layers:

$$\begin{aligned} f_S &: \mathbb{R}^m \times \mathbb{R}^h \to \mathbb{R}^h \\ f_O &: \mathbb{R}^h \to \mathbb{R}^n \end{aligned}$$

The vector space $\mathbb{R}^h$ is the h-dimensional state space, and $\mathbb{R}^n$ is the n-dimensional output space. The function f_S computes the next state and f_O computes the final output.

Given an input sequence $(x_1, x_2, \dots, x_L)$, and an initial $s_0 \in \mathbb{R}^h$, we compute a sequence of states $(s_1, s_2, \ldots, s_L)$, where

$$s_i = f_S(x_i, s_{i-1}) \text{ for } i \in [1, L]$$

Thus, for each step i, s_i indirectly depends on $x_1, x_2, \ldots x_i$.

The final output is given by:

$$y = f_O(s_L)$$

We can design f_S and f_O using general vector-to-vector layers (such as MLP). See the survey [**yu2019review**] for different design possibilities.

RNNs can also be "unrolled" in time to remove cycles from its graph. It can be conceptualized as copying the network for each time step along the input sequence, with the same weights shared. This means that RNNs can process inputs of any length and make predictions at any point in the sequence. The training of RNN is challenging because unrolling creates numerical challenges to the gradient optimization algorithms.

Generally speaking LSTM (long short term memory) is considered the most numerically effective design to implement an RNN.

2.4.5 Convolution in sequence learning

1D convolution is a mathematical operation that takes two input signals and produces a third output signal. In the context of natural language processing (NLP), 1D convolution can be used to process text data. The input signals are typically the words or characters in a sentence, and the output signal is a new representation of the sentence that is more useful for downstream tasks such as sentiment analysis or named entity recognition (NER).

To define the 1D convolution operation, we need to make a few auxiliary definitions.

Consider a sequence of length L of scalar values: $\vec{x} = (x_1, x_2, \dots x_L) \in \mathbb{R}^L$.

- **l-window**: at each position in the sequence $1 \leq i \leq L$, the l-window is defined as $x_i, x_{i+1}, \dots x_{i+l-1}$. It is the consecutive sequence from i to $i + l - 1$. We will denote it as $x[i : i + l - 1] \in \mathbb{R}^l$.

- **Kernel**: a *kernel* K is a sequence of length l where $l < L$.

- **Convolution**: is a process of generating a sequence of outputs $\vec{y} = (y_1, y_2, \dots y_{L-l+1})$ of length $L - l + 1$. It is given by:

  $$y_i = \langle x[i : i + l - 1], K \rangle = \sum_{j=1}^{l} x[i + j - 1] \cdot K[j]$$

  Namely, $\vec{y} = \vec{x} * K$.

The convolution layer generalizes 1D convolution in two important ways:

1. Multidimensional input vectors: each x_i is a vector in $\mathbb{R}^m$. Thus, each y_i is the sum of the scalar convolutions:

   $$y_i = \sum_{j=1}^{l} \langle x[i + j - 1], K[j] \rangle$$

2. Multiple kernels are used to generate multidimensional output vectors: With n

kernels $K_1, K_2, \dots K_n$, for each window i, we generate:

$$y_i = \begin{bmatrix} \langle x[i:i+l-1], K_1 \rangle \\ \langle x[i:i+l-1], K_2 \rangle \\ \vdots \\ \langle x[i:i+l-1], K_n \rangle \end{bmatrix}$$

Thus, with n kernels, the 1D convolutional layer maps an input sequence of $\mathbb{R}^m$ vectors to an output sequences of $\mathbb{R}^n$ vectors. The n kernels with window size l are the model parameters.

A complete convolutional neural network (CNN) requires some additional features:

- **Non-linear activation function**. The output $\mathbf{conv}(x, K)$ is processed by a non-linear activation function σ:

$$y = \sigma(\mathbf{conv}(x, K))$$

- **Padding and pooling**. By default the convolution layer changes the sequence length L to $(L-l+1)$. Padding is to augment the initial sequence with additional $l-1$ special boundary vectors such that the length of convolution output is L. Padding is to preserve the sequence length during convolution. Pooling is to aggregate each w-window to a single value. Thus, pooling with a stride of w is to convert a sequence of length L to $\lfloor L/w \rfloor$. Together, padding and pooling allows us to fine control the output sequence length of the convolution layer.

- **Output linear layer**. The final output of the CNN is a probability distribution of $p \in \mathbb{R}^c$ if we are to perform a c-category classification task. A linear layer is used to convert $\lfloor L/w \rfloor \times n$ output from the convolution/pooling layer to size c.

2.4.6 Attention and transformer models

Attention is a mechanism used in some neural networks to allow a model to focus on certain parts of its input. This allows the model to handle inputs of variable length and to learn to weight different parts of the input differently. For example, in natural language processing (NLP), attention mechanism can be used to allow a model to focus on certain words in a sentence to better understand its meaning.

Given a finite set of vectors, $X = \{x_1, x_2, \ldots x_n\} \subseteq \mathbb{R}^m$, the (self) attention layer processes all the vectors in X simultaneously:

$$(y_1, y_2, \ldots y_n) = \mathbf{Attention}(x_1, x_2, \ldots, x_n)$$

where each input vector x_i is transformed to its respective attended output y_i. The output y_i should capture information about x_i *augmented* by other input vectors that x_i *attends* to. For example, if $\{x_i\}$ forms a sequence, then it's possible for x_i to pay attention to its immediately adjacent vectors $\{x_{i-1}, x_{i+1}\}$. The attention layer dynamically computes the attention and the attended output for *each* input vector x_i.

The attention is modeled by a $n \times n$ matrix of attention scores:

$$a_{ij} = \mathbf{AttentionScore}(x_i, x_j) \in [0, 1]$$

A popular approach to compute the attention score is to learn latent representations known as keys and queries of each x_i using simple linear layers:

- $k_i = W_1 x_i + b_1 \in \mathbb{R}^d$
- $q_i = W_2 x_i + b_2 \in \mathbb{R}^d$

The key and query vectors belong to the same vector space, and their scaled inner products give us the attention score:

$$a_{ij} = \text{softmax}_j \left(\frac{\langle q_i, k_j \rangle}{\sqrt{d}} \right)$$

Finally, the attended output y_i is the linear combination of $\{x_i\}$ with the attention scores as the mixture coefficients:

$$y_i = \sum_j a_{ij} x_i$$

Transformer models are based on neural network architectures that use attention mechanisms extensively. The original transformer model was introduced in a paper by Vaswani et al. [**DBLP:journals/corr/VaswaniSPUJGKP17**] in 2017. It was considered a major advance in the field of NLP, and since then various transformer-based models have appeared and been widely used in NLP tasks. Transformer models are notable for their ability to process input sequences in parallel, which makes them much faster to train and evaluate than other models.

2.4.7 MLP Mixer

MLP Mixer [**tolstikhin2021mlp**] is a neural network that processes multi-channel inputs in two stages: token mixing followed by channel mixing.

The input to a MLP mixer is a fixed-length sequence of feature vectors:

$$\vec{x} = (x_1, x_2, \ldots, x_L)$$

where each $x_i \in \mathbb{R}^C$, and L is the length of the sequence. C is the number of channels. Each x_i is a feature of a token consisting of C channels of scalars. Collectively we have $\vec{x} \in \mathbb{R}^{L\times C}$.

In order to explain token mixing and channel mixing, we need to introduce the notation of *distributed* function application first.

Suppose we have two functions, $f : \mathbb{R}^m \to \mathbb{R}^m$ and $g : \mathbb{R}^L \to \mathbb{R}^L$. Given a matrix $X \in \mathbb{R}^{L\times m}$, its column vectors are in $\mathbb{R}^L$, and its row vectors are in $\mathbb{R}^m$. Therefore, we can apply f to row vectors, and g to column vectors. This creates two possible outputs by *distributedly* applying f and g.

$$\begin{aligned} U[i,:] &= f(X[i,:]) \text{ for all } i \in [1, L] \\ V[:,j] &= g(X[:,j]) \text{ for all } j \in [1, m] \end{aligned}$$

In MLP mixer, the input $\vec{x}$ will be processed by two separate MLPs: the first MLP is distributed along its tokens (token mixing), and then the second MLP is distributed along the channels (channel mixing). The MLP mixer mixes the output of the two mixing MLPs back to the original feature vectors.

The first stage, token mixing, produces the output defined by:

$$U[:,j] = \vec{x}[:,j] + W_2\sigma(W_1\vec{x}[:,j])$$

where W_1, W_2 are the matrices of the first MLP.

The second stage, channel mixing, produces the output by distributing the second MLP:

$$Y[i,:] = U[i,:] + W_4\sigma(W_3U[i,:])$$

where W_3, W_4 are the matrices of the second MLP.

The mixing MLPs do not use any bias vectors.

As demonstrated [**tolstikhin2021mlp**], MLP mixer exhibits many desirable qualities such as faster training time for very large training datasets, smaller model size when compared to very large computer vision models, and finally its performance is nearly and sometimes exceeds state-of-the-art models in many vision tasks.

Chapter 3

Search Algorithm and Neural Network Accelerated Indexing

In this chapter, we define our problem and present our proposed solution.

Problem statement: We want to extend keyword search to relational data using full-text index with the help of an embeddable neural network that optimizes the query processing pipeline. Given a relational database consists of K relations $R_1, R_2, R_3, \ldots, R_K$, the goal is to build a system that takes a partial tuple as user query and can find an optimally matching complete tuple $\vec{r} \in R_i$ ($i \in \{1, 2, \ldots, K\}$) efficiently.

3.1 Problem definition of partial tuple search

In this section, we provide some definitions related to partial tuple search. Let R be a relational table. Recall that attr(R) is the attributes of R, and tuples in R are mappings from attr(R) to **Values**.

Definition 3 (Labeled values and partial tuple)**.** *Let R be a relational table. A labeled* *value in R is a pair $(l : x)$ where $l \in \mathrm{attr}(R) \cup \{?\}$ and $x \in$ **Values**. A partial tuple $\vec{x}$ is a set of labeled values: $\vec{x} = \{(l_i, x_i) : i \in I\}$. We define the attributes of a partial tuple $\vec{x}$ as the labels of the partial tuple:*

$$\mathrm{attr}(\vec{x}) = \{l_i\}_{i \in I}$$

*. A partial tuple is considered **complete** if $\mathrm{attr}(\vec{x}) = \mathrm{attr}(R)$.*

We will write $\vec{x}[l_i]$ to denote the corresponding value x_i.

Note that a partial tuple is a set of values and their respective attribute names from a relational table. However, we allow a special symbol "?" to be in place of the attribute name. The special attribute "?" indicates that the attribute name is unspecified (or unknown). The following example illustrates two partial tuples. The second partial tuple has a wild card "?" as its attribute name:

Example 6.

$$\begin{aligned} \vec{s}_1 &= \{\mathrm{name} : \mathrm{Einstein}\} \\ \vec{s}_2 &= \{\mathrm{name} : \mathrm{Einstein},\ ? : \mathrm{Professor}\} \end{aligned}$$

A query is a partial tuple: $\vec{Q} = \{(l_i, q_i) : i \in I_Q\}$. The values q_i are keyword queries. We want to find a complete tuple $\vec{r} \in R$ that matches $\vec{Q}$ optimally. This requires us to define how to compare the partial tuple $\vec{Q}$ with a complete tuple $\vec{r}$. The guiding principle of comparing the two tuples is to match labeled values from $\vec{Q}$ with those from $\vec{r}$ according to the following:

- Match the labels if they are not the wild card "?".

- Match the values using a fuzzy string matching score.

- Optimize the sum of similarities between labeled values from $\vec{Q}$ and those from $\vec{r}$.

Towards this end, we define the following similarity measures:

Definition 4 (Similarity of labeled values)**.** *Consider two labeled values: $(l_1 : x_1)$ and (l_2, x_2), where l_1 and l_2 are two labels from* $\mathrm{attr}(R) \cup \{?\}$*. The similarity between the two labels l_1 and l_2 is given by:*

$$\mathrm{sim}(l_1, l_2) = \begin{cases} 1 & \text{if } l_1 = l_2 \text{ and } l_1 \neq ?,\ l_2 \neq ? \\ 0 & \text{if } l_1 \neq l_2 \text{ and } l_1 \neq ?,\ l_2 \neq ? \\ 0.5 & \text{if } l_1 = ? \text{ or } l_2 = ? \end{cases}$$

Thus, whenever l_i is the wildcard "?", the similarity is 0.5. Otherwise, it is determined by the equality comparison of the two labels.

The similarity between the two values x_1 and x_2 is based on string comparison. We utilize the Jaccard similarity between the 3-grams of x_i:

$$\mathrm{sim}(x_1, x_2) = \mathrm{Jaccard}(\mathrm{3grams}(x_1), \mathrm{3grams}(x_2))$$

Finally, the similarity of the two labeled values is computed as the product of the similarity between labels and similarity between values.

$$\mathrm{sim}((l_1 : x_1), (l_2, x_2)) = \mathrm{sim}(l_1, l_2) \cdot \mathrm{sim}(x_1, x_2)$$

Recall that the user query is a partial tuple $\{(l_i, q_i) : i \in I_Q\}$, and the search results are complete tuples of the form $\{(l_j, v_j) : j \in I_R\}$. We need to generalize the similarity measure in Definition **??** to partial tuples.

Definition 5 (Similarity of partial tuples)**.** *Given two tuples: $\vec{q} = \{(l_i, q_i) : i \in I_Q\}$*

and $\vec{r} = \{(l_j, v_j) : j \in I_R\}$. *We define their similarity based on the optimal matching of labeled values from* $\vec{q}$ *to* $\vec{r}$.

Let $H \subseteq I_Q \times I_R$ *be the optimal matching that maximizes the total similarity score. The similarity of two tuples is given as:*

$$\mathrm{sim}(\vec{q}, \vec{r}) = \sum_{(i,j)\in H} \mathrm{sim}((l_i, q_i), (l_j, v_j))$$

Note that in order to compute the similarity between a query $\vec{q}$ and a complete tuple $\vec{r}$, we need to first compute the similarities between labeled values from $\vec{q}$ and those from $\vec{r}$. Then we find optimal matches from $\vec{q}$ to $\vec{r}$, and use those to get the total similarity score.

Definition 6 (Partial tuple search)**.** *Let* $R_1, R_2, R_3, \ldots, R_K$ *be* K *relations. Given a user query that is a partial tuple:*

$$\vec{Q} = \{(l_i, q_i) : i \in I_Q\}$$

where $l_i \in attr(R) \cup \{?\}$ *and* q_i *are keyword queries, we want to find a complete tuple* $\vec{r} \in R_i,\ i \in \{1, 2, \ldots, K\}$, *that maximizes the similarity score* $\mathrm{sim}(\vec{Q}, \vec{r})$.

The process of partial tuple search, illustrated in Figure **??**, consists of encoding partial tuple queries, searching full-text indexes, and find optimal matching among search results for the partial tuple. We provide detailed descriptions about partial tuple search in Section **??**.

We use a neural network to optimize the query processing pipeline. Detailed description can be found in Section **??**. We define the neural network classifier as:

Definition 7 (Neural network classifier)**.** *Let* $R_1, R_2, R_3, \ldots, R_K$ *be* K *relations. The neural network classifier takes a partial tuple query* $\vec{q}$ *and estimates the probabilities*

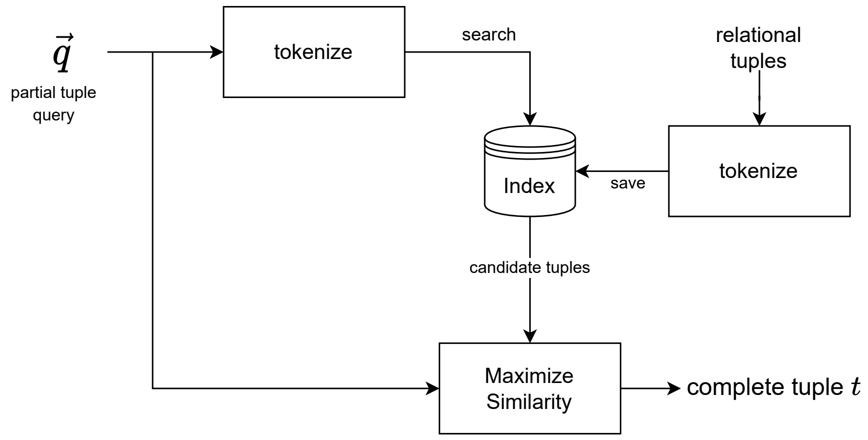


Figure 3.1: Matching a partial tuple $\vec{q}$ to a complete tuple t

that the search result of $\vec{q}$ belongs to relation R_i, $\forall i \in \{1, 2, \ldots, K\}$.

3.2 Partial tuple search using full-text search

Traditional full-text indexes, such as Apache Lucene, support keyword queries over large document collections using an inverted index data structure. In this section, we describe how a full-text index is incorporated as the first stage of the query processing pipeline for partial tuple search.

The advantages of using a full-text index are:

- Flexible and partial string matching between query keywords and document text
- Efficient query processing provided that the inverted document lists are not too long due to collisions.

We first encode complete relational tuples as documents to be stored in the full-text index. The partial tuple query $\vec{q}$ is encoded as a keyword query. It is important to point out that we must specify the same tokenizer to convert relational tuples and query tuples to tokenized terms. We use the 3-gram tokenizer to support fuzzy string matching for the values.

The full-text index evaluates the keyword query, and computes a top-k result set of the best matching documents as relational tuple candidates. These top-k candidates guarantee high similarity between the labeled values in $\vec{q}$ and those in relational tuples.

3.2.1 Encoding of tuples as documents

Let us denote the tokenizer function as **tokenize**. A tuple $\vec{r}$ is converted into a document doc as follows:

$$\mathrm{attr}(\mathrm{doc}) = \mathrm{attr}(\vec{r}) \cup \{\texttt{fulltext}\}$$

For each $a \in \mathrm{attr}(\vec{r})$,

$$\mathrm{doc}[a] = \textbf{tokenize}(\vec{r}[a])$$

Also,

$$\mathrm{doc}[\texttt{fulltext}] = \bigcup \left\{\textbf{tokenize}(\vec{r}[a]) : a \in \mathrm{attr}(\vec{r})\right\}$$

The special field `fulltext` of doc contains all tokenized terms of the tuple $\vec{r}$.

Example 7. Given a tuple $\vec{r}$ as:

$$(\mathrm{Name} : \textit{Jack},\ \mathrm{Address} : 100\ \textit{Simcoe Street})$$

Its attributes $\mathrm{attr}(\vec{r})$ are $\{\mathrm{Name}, \mathrm{Address}\}$. Therefore, the document attributes $\mathrm{attr}(doc)$ are $\{\mathrm{Name},\ \mathrm{Address},\ \mathrm{fulltext}\}$.

If we use a standard tokenizer, the result of tokenization will be,

$$\left[\begin{array}{rcl} \text{Name} & \mapsto & \text{Jack} \\ \text{Address} & \mapsto & \text{100, Simcoe, Street} \\ \text{fulltext} & \mapsto & \text{Jack, 100, Simcoe, Street} \end{array}\right]$$

On the other hand, if we use a character-based 3-gram tokenizer with a special padding character "_", the result will be,

$$\left[\begin{array}{rcl} \text{Name} & \mapsto & \text{\_\_J \_Ja Jac ack ck\_ k\_\_} \\ \text{Address} & \mapsto & \text{\_\_1 \_10 100 00\_ 0\_\_ \_\_S \_Si Sim imc mco coe oe\_ e\_\_ \_\_S \_St Str tre ree eet et\_ t\_\_} \\ \text{fulltext} & \mapsto & \text{\_\_J \_Ja Jac ack ck\_ k\_\_ \_\_1 \_10 100 00\_ 0\_\_ \_\_S \_Si Sim imc mco coe oe\_ e\_\_ \_\_S} \\ & & \text{\_St Str tre ree eet et\_ t\_\_} \end{array}\right]$$

3.2.2 Encoding partial tuple queries as keyword queries

Given a partial tuple $\vec{q}$, we want to encode it as a keyword query such that the search engine can find the documents that correspond to the relevant tuples.

For each labeled value (l_i, x_i) in the partial tuple, we generate a query clause.

- If $l_i \neq ?$, then the query clause is $q_i = l_i : x_i$.
- If $l_i = ?$, then the query clause is $q_i = \texttt{fulltext} : x_i$.

The generated query is:

$$q = q_1 \textbf{ or } q_2 \textbf{ or } \ldots$$

One can see that any complete tuple $\vec{r}$ that satisfy the query $\vec{q}$ will have its encoding document satisfying the keyword query q.

3.2.3 From search results to partial tuple completion

For our problem, we need to match the partial tuple $\vec{q}$ with a complete tuple t. This can be done by further post-process the documents in search results returned by the search engine.

Recall that a tuple matching is a function $h : \mathrm{LV}(\vec{q}) \to \mathrm{LV}(t)$, where $\mathrm{LV}(\vec{q})$ and $\mathrm{LV}(t)$ are labeled values of $\vec{q}$ and t, respectively. The top completion of $\vec{q}$ should be a complete tuple that has the highest matching score based on the similarity measure. Since the search engine already returns the top-k candidate documents, we can compute the optimal matching between $\vec{q}$ to each of the candidates in order to rank the candidates with respect to their matching scores.

Finding optimal matching of labeled values from the partial tuple $\vec{q}$ to a candidate tuple t is equivalent to solving the maximum weighted matching of a bipartite graph.

Define the graph G as:

- The vertices are: $V = \mathrm{LV}(t) \cup \mathrm{LV}(\vec{q})$.
- The edges and their respective weights are defined as:

  $$E = \{\langle x_1, x_2, \mathrm{sim}(V(x_1), V(x_2)\rangle : x_1 \in \mathrm{LV}(t) \text{ and } x_2 \in \mathrm{LV}(\vec{q}) \text{ and } (L(x_1) = L(x_2) \text{ or } L(x_2) = ?)\}$$

  where $L(x_1)$ and $L(x_2)$ are labels of x_1 and x_2, respectively.
- G is the weighted graph (V, E).

The max-weighted matching of G is necessarily a matching h from $\mathrm{LV}(\vec{q})$ to $\mathrm{LV}(t)$. The weight sum of h is the matching score based on the similarity of matched labeled values. It is now that the optimal matching can be found exactly in polynomial time using various algorithms, e.g., Hungarian algorithm [**cormen2022introduction**].

3.3 Optimizing query processing pipeline with neural networks

As described in Section **??**, a potential bottleneck associated with inverted index structures for full-text search is the hashing collision which creates long linked lists at the leaf nodes of the index tree (See Figure **??**).

In our application, the character based 3-gram tokenizer will generate a compact vocabulary consisting of at most $|\mathrm{charset}|^3$ distinct tokens where charset is the total character set. So, when the number of documents grow greater than $|\mathrm{charset}|^3$, the linked lists at the leaf nodes will grow linearly with respect to the number of relational tuples.

The concern is that the full-text index will degrade as the dataset size grows due to the 3-gram tokenization that we employ to support fuzzy string matching. Unfortunately, our experimental evaluation in Section **??** confirms the performance degradation in practice.

In this section, we will describe a method to perform partitioning of the full-text index to overcome the performance bottleneck caused by hash collisions.

Our method utilizes a neural network to optimize the index access order during partial tuple search. The neural network is to be embedded in the overall query processing pipeline, and will be self-supervised based on existing data.

3.3.1 Partition of full-text index

An aggregated index is a function as follows:

$$\mathbf{index} : \mathbf{Query} \to \mathbf{List}[\mathbf{Tuple}]$$

It indexes all the tuples from every relation.

However, we advocate to partition the tuples based on the relation they below to. Thus, if we have relations $R_1, R_2, R_3, \ldots, R_n$, we will have n indexes $\{\mathbf{index}_1$, $\mathbf{index}_2$, ..., $\mathbf{index}_n\}$, each indexing the tuples of a single relation.

$$\mathbf{index}_i : \mathbf{Query} \to \mathbf{List}[\mathbf{Tuple}]$$

The search can be done concurrently over all indexes:

```
priority_queue
for index_i in all_indexes {
  spawn index_i.search(q) into priority_queue
}
```

We can also do sequential access of the indexes:

```
for index_i in sorted(all_indexes, q) {
    index_i.search(q) into priority_queue
}
```

In this thesis we focus on the sequential access approach in favour of saving CPU load. The challenge is to sort the indexes dynamically based on the user query $\vec{q}$. The sorting should place relations that can satisfy $\vec{q}$ with higher priority, so that successful matches are found as early as possible.

Thus, our strategy to sort the indexes is based on a sorting key function:

$$S : (\mathbf{index}_i, \vec{q}) \to [0, 1] \mapsto \mathbf{prob}(\mathrm{result}(\vec{q}) \in R_i)$$

The sorting score $S(\mathbf{index}_i, \vec{q})$ is the (estimate of the) probability that the search result of $\vec{q}$ belongs to the relation R_i. Since there are only a finite many relations, we can reformulate the scoring function S to as an n-way classification function:

$$\textbf{classify} : \vec{q} \mapsto \begin{bmatrix} S(\textbf{index}_1, \vec{q}) \\ S(\textbf{index}_2, \vec{q}) \\ \vdots \\ S(\textbf{index}_n, \vec{q}) \end{bmatrix}$$

Our objective is to learn the **classify** function using a neural network.

3.3.2 Vectorization of queries

The classifier can be trained using a neural network that can be embedded in the query processing pipeline. The design objectives are:

- The neural network must be compact in size so that it incurs minimal performance overhead, and can be embedded in a search system.
- The training of the network must require minimal manual intervention. Thus the neural network must be trained with self-supervision from existing data.

The classification function is:

$$\textbf{classify} : \textbf{Query} \to \mathbb{R}^n \tag{3.1}$$

where the output of **classify** is the probability distribution over the n partitioned indexes. Elements we presented in Section **??** present several options for the neural network architecture.

Token representation of queries: given a query $\vec{q} = \{(l_i, x_i) : 1 \leq i \leq m\}$, we generate the text representation of the query by simply concatenating the text representation of labels and the tokenized query values.

$$\mathbf{tokens}(\vec{q}) = \{l_1\} \oplus \mathbf{tokenize}(x_1) \oplus \{l_2\} \oplus \mathbf{tokenize}(x_2) \oplus \ldots \{l_m\} \cup \mathbf{tokenize}(x_m)$$

where $\oplus$ is sequence concatenation.

Integer encoding of queries: next we encode $\mathbf{tokens}(\vec{q})$ using a universal vocabulary **vocab**. The vocabulary consists of all known tokens, and their respective ordinal integer code. This vocabulary will be built using the existing relational tuples. The construction of the vocabulary is described in subsequent sections. The vocabulary is described as a function from tokens to integers:

$$\mathbf{vocab} : \mathbf{Token} \to \mathbb{N}$$

The integer sequence of a query is given by:

$$\mathbf{sequence}(\vec{q}) = \mathbf{vocab} \circ \mathbf{tokens}(\vec{q}) \in \mathbb{N}^*$$

Embedding vectors of queries: Using a standard embedding layer (Section **??**), embed the integer sequence representation of the query to a sequence of latent vectors.

$$\mathbf{vector}(\vec{q}) = \mathbf{Embedding}(\mathbf{sequence}(\vec{q})) \in \mathbb{R}^{|q| \times d}$$

At this point, we have many options in mapping the vector sequence to the probability distribution in $\mathbb{R}^n$.

For the remainder of this chapter, we denote the vector sequence representation of $\vec{q}$ as:

$$\vec{x} = \mathbf{sequence}(\vec{q}) = (x_1, x_2, \ldots, x_{|q|})$$

where each $x_i \in \mathbb{R}^d$ is the embedding vector of the i-th token in a d-dimensional latent space.

3.3.3 Neural network architectures for query classification

MLP based classification.

Given the input of vectorized query representation $\vec{x}$, we first flatten it using global average over the entire sequence length. Then, we process it with a MLP with softmax activation function. The MLP must have n output neurons.

$$\begin{array}{rlr}
 & \vec{x} & (|q|, d) \\
\rightarrow & \left(\frac{\sum_{i=1}^{|q|} x_i}{|q|}\right) & (d) \\
\rightarrow & \mathbf{MLP}(\text{output-dim} = n) & (n) \\
\rightarrow & \mathbf{softmax}(\cdot) & (n)
\end{array}$$

Recurrent network architecture with LSTM cells.

Since recurrent neural networks (RNN) are specifically designed to process sequence inputs, we can utilize a RNN to map the input $\vec{x}$ to a flattened state vector, which can then be processed by a MLP to compute the output probability distribution.

The advantage of RNN is that it can learn inter-token dependencies in the query at the cost of a bigger model size and higher training cost.

$$\begin{array}{rll}
 & \vec{x} & (|q|, d) \\
\rightarrow & \textbf{LSTM}(\text{output-state=True}) & (d) \\
\rightarrow & \textbf{MLP}(\text{output-dim} = n) & (n) \\
\rightarrow & \textbf{softmax}(\cdot) & (n)
\end{array}$$

1D convolution architecture.

Another standard technique to learn sequential features is to use 1D convolution. The 1D convolution layer (Section **??**) produces a sequence of *feature* vectors that capture the short-range token dependencies within the convolution window size. We then use global averaging to flatten the convolution features for further processing using a MLP.

$$\begin{array}{rll}
 & \vec{x} & (|q|, d) \\
\rightarrow & \textbf{Conv1D} & (|q|, d) \\
\rightarrow & \textbf{Global Average} & (d) \\
\rightarrow & \textbf{MLP}(\text{output-dim} = n) & (n) \\
\rightarrow & \textbf{softmax}(\cdot) & (n)
\end{array}$$

Transformer and MLP Mixer

Transformers have shown to be a superior architecture for many tasks in the domain of MLP and sequence learning. The exact architecture of a transformer block is shown in the implementation section (See Figure **??**). Due to the nature of our problem, we chose to use only a single transformer block so that the model remains small enough to be embedded in the query processing pipeline.

A more recent MLP based architecture is MLP mixer which is a concatenation of two MLP layers separated by a matrix transpose operation. Details of the MLP mixer are shown in Figure **??**.

3.3.4 Unsupervised training of neural network classifiers

The classifier needs to be trained with data of the following form:

$$(\vec{q}, i)$$

where $\vec{q}$ is a sample query, and i is the relation R_i that contains the best matching tuple of $\vec{q}$.

The training data is generated directly from the relational tuples from the database. For each complete tuple $\vec{r} = \{(l_i, x_i) : i \in I\}$, we formed a query $\vec{q_r}$ by random sampling from the labeled values while masking the labels.

$$\vec{q_r} = \{(?, x_i) : i \in \mathbf{sample}(I)\}$$

Thus, given a database with n relations $R_1, R_2, \ldots, R_n$:

$$\mathbf{train} = \bigcup_{i=1}^{n} \{(\vec{q_r}, i) : r \in R_i\}$$

3.4 Overall query processing pipeline

To summarize the proposed query processing pipeline for partial tuple search, we have the following stages:

1. A partial tuple is entered as user input.
2. The partial tuple is tokenized and converted to a structured keyword query.
3. The neural network classifier sorts the partitioned indexes based on the probability scores.

4. The partitioned indexes are scanned to find top-k complete tuple candidates from the database.

5. The candidates are ranked by max-matching based similarity scores.

Our pipeline requires that partitioned full-text indexes are built from tuples of each relation in offline mode. In addition, the neural network classifier should be trained using sampled tuples from each relation.

In Chapter **??**, we will describe the implementation of each neural network architecture. We will also discuss the experimental evaluation and comparison of the performance gain of each neural network architecture.

Chapter 4

Implementation and Performance Evaluation of Neural Networks For Index Acceleration

In the previous chapter, we have presented the neural network based algorithm to accelerate the partial tuple search of relational data. Our algorithm relies on a partial tuple classifier to optimize the ordering of text index search. In particular, we have shown that a variety of neural network architectures can be used in the design of the classifier.

In this chapter, we will describe the evaluation of the proposed solutions. We will verify the effectiveness and limitations of our solutions, and perform a comparative study of different network architectures. For each network architecture, we will present the benefits and drawbacks, and provide our understanding of the explanation of the observations.

4.1 Some assumptions about datasets

In this section, we list some assumptions for our experimental evaluation:

- The numbers of tuples of relations are not skewed, this is, there is no relation that has an extremely large number of tuples than other relations.

- Applying operations of inserting new tuples, updating or deleting existing tuples to a database does not introduce new vocabulary.

These assumptions imply limitations of our proposed solutions. We will provide some discussion about the limitations and possible future work in Section **??**.

4.2 Datasets

The datasets we have used to evaluate our system is a collection of survey data from Statistics Canada [**ds01**, **ds02**, **ds03**, **ds04**, **ds05**, **ds06**, **ds07**, **ds08**, **ds09**, **ds10**], which includes one labour force survey, six COVID-19 surveys, one income survey, one community health survey, and one housing survey. They offer many real-world characteristics that pose as challenges to neural network classifiers. Given the intended application scenarios of our research, we felt that it was important to evaluate our work using real-world datasets. For easy reference in subsequent sections, we give each dataset an id, as shown in Table **??**.

These 10 datasets contain both numerical and textual data with different numbers of attributes and tuples. For example, the labour force survey contains data of the Canadian labour market. It has total 60 attributes related to the job market, such as employment status, industry, status of working full-time or part-time, hourly wage, etc. Table **??** shows 5 samples with a subset of 10 attributes. The descriptions of

Dataset id	**Dataset name**
ds01	Labour Force Survey, April 2019 [Canada]
ds02	Crowdsourcing: Impacts of COVID-19 on Canadians' Experiences of Discrimination Public Use Microdata File
ds03	Crowdsourcing: Impacts of COVID-19 on Canadians Public Use Microdata File, [2020]
ds04	Crowdsourcing: Impacts of the COVID-19 on Canadians – Your Mental Health Public Use Microdata File, [2020]
ds05	Crowdsourcing: Impacts of COVID-19 on Canadians' Perception of Safety Public Use Microdata File, [2020]
ds06	Crowdsourcing: Impacts of the COVID-19 on Canadians – Trust in Others Public Use Microdata File [2020]
ds07	Impacts of the COVID-19 pandemic on postsecondary students (ICPPS) 2020, Crowdsource file, Public use microdata file
ds08	Canadian Income Survey (CIS), 2017
ds09	Canadian Community Health Survey - Annual Component (CCHS) 2017-2018
ds10	Canadian Housing Survey, 2018

Table 4.1: Dataset ids and names

survyear	**survmnth**	**lfsstat**	**prov**	**age_12**	**educ**	**immig**	**noc_10**	**ftptmain**	**hrlyearn**
2019	April	Employed, at work	Ontario	25 to 29 years	Postsecondary certificate or diploma	Non-immigrant	Natural resources, agriculture and related production occupations	Full-time	33.00
2019	April	Not in labour force	British Columbia	70 and over	Bachelor''s degree	Non-immigrant			
2019	April	Employed, at work	British Columbia	45 to 49 years	High school graduate	Non-immigrant	Business, finance and administration occupations	Full-time	26.00
2019	April	Employed, at work	Ontario	20 to 24 years	Postsecondary certificate or diploma	Non-immigrant	Health occupations	Full-time	37.60
2019	April	Employed, at work	Ontario	70 and over	Some postsecondary	Immigrant, landed more than 10 years earlier	Occupations in art, culture, recreation and sport	Part-time	32.00

Table 4.2: 5 samples from the labour force survey dataset "ds01", showing only 10 attributes.

the selected 10 attributes are shown in table **??**. Table **??** shows the number of attributes and tuples in each dataset.

Sometimes different datasets share common attributes. For example, the COVID-

Attribute	**Description**
survyear	Survey year
survmnth	Survey month
lfsstat	Labour force status
prov	Province
age_12	Five-year age group of respondent
educ	Highest educational attainment
immig	Immigration status
noc_10	2016 NOC (10 categories)
ftptmain	Full- or part-time status at main or only job
hrlyearn	Usual hourly wages, employees only

Table 4.3: 10 attributes and their descriptions from the labour force survey dataset “ds01”.

Dataset id	**No. of attrs.**	**No. of tuples**
ds01	60	100,885
ds02	129	36,662
ds03	47	242,512
ds04	43	45,989
ds05	23	43,631
ds06	47	36,538
ds07	42	101,902
ds08	194	92,286
ds09	1051	113,286
ds10	132	61,750

Table 4.4: Number of attributes and tuples in each dataset.

19 datasets have a common attribute about community size and metropolitan influence zones where the survey correspondents live in. By using multiple partial tuple completion, users can “jump” from one dataset to another. For example, users may find some data related to discrimination from the dataset of impacts of COVID-19 on Canadians’ experiences of discrimination. Then they can use the results to search more information about people’s perception of safety in the communities with the same sizes in the dataset of impacts of COVID-19 on Canadians’ perception of safety. This will help users to gain more insights from the survey results.

4.3 Architecture and software stack

In order to thoroughly evaluate the end-to-end search system, we have developed a platform with the following technology stack. We use Lucene [**lucene**] as the full-text index. A customized search engine is developed on top of Lucene to support partial tuple search queries. This is necessary for us to have detailed instrumentation to collect performance metrics, and to gain control over the ordering of text index search. We have implemented all neural network based classifiers using TensorFlow [**tensorflow**]. The trained models are used to generate the ordering of Lucene index access. The evaluation of the neural network acceleration is based on the speed-up of query performance between the machine learning generated ordering and other alternatives. In addition, top-k accuracy is also used to evaluate models. The query workloads used in evaluation are generated from the datasets themselves. Figure **??** shows the high-level architectural overview of our implementation. More details about the training datasets and the query workload generation will be presented in subsequent sections.

4.3.1 Lucene and a customized search engine

We developed a customized search engine on top of Lucene. It has two main functions. The first is to index datasets to create Lucene indexes. When indexing datasets, each tuple is converted to a Lucene document, which contains a set of *(attribute name, attribute value)* pairs. We apply character-based 3-gram tokenization to attribute values. We use the special character "_" for padding. In addition, we add an extra field "fulltext" to the document, which contains all 3-gram tokens of all attribute values. This field is needed to support full-text search. For example, given a tuple t

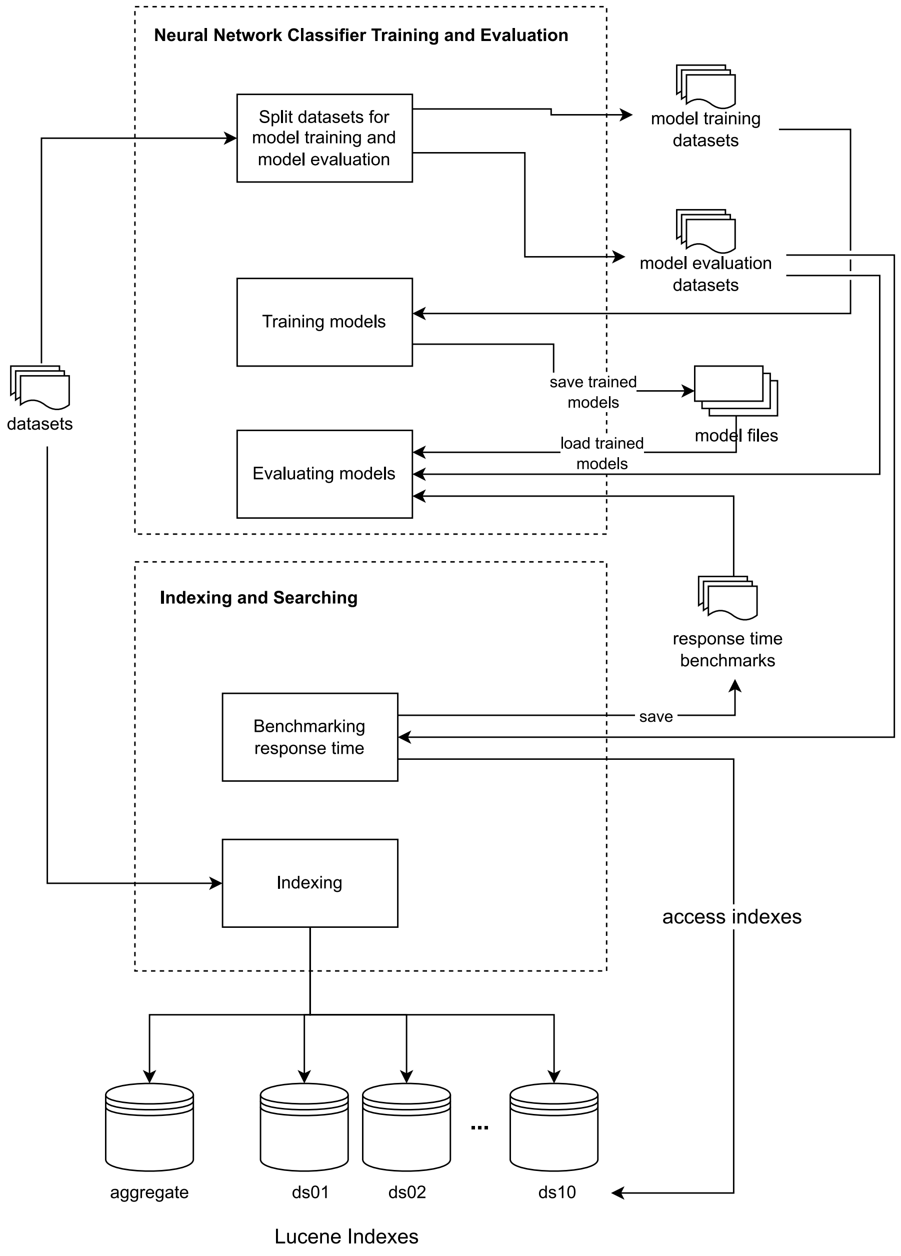


Figure 4.1: High-level overview of architecture

as,

$$\{\text{Name} : Jack,\ \text{Gender} : Male,\ \text{Occupation} : \text{Software developer}\}$$

our search engine will first apply Lucene's standard tokenization, and then our character-based 3-gram tokenization. The resulting Lucene document will be,

$$\left[\begin{array}{rl} \text{name}: & \_\_j\ \_ja\ jac\ ack\ ck\_\ k\_\_ \\ \text{gender}: & \_\_m\ \_ma\ mal\ ale\ le\_\ e\_\_ \\ \text{occupation}: & \_\_s\ \_so\ sof\ oft\ ftw\ twa\ war\ are\ re\_\ e\_\_\ \_\_d\ \_de\ dev\ eve\ vel \\ & elo\ lop\ ope\ per\ er\_\ r\_\_ \\ \text{fulltext}: & \_\_j\ \_ja\ jac\ ack\ ck\_\ k\_\_\ \_\_m\ \_ma\ mal\ ale\ le\_\ e\_\_\ \_\_s\ \_so\ sof \\ & oft\ ftw\ twa\ war\ are\ re\_\ e\_\_\ \_\_d\ \_de\ dev\ eve\ vel\ elo\ lop\ ope \\ & per\ er\_\ r\_\_ \end{array}\right]$$

The second main function is to support partial tuple search queries. We also use character-based 3-gram tokenization when constructing a search query. For example, given a partial tuple as:

$$\{\text{Name}: Jack,\ \text{Gender}: Male\}$$

the search query will be:

$$\{\text{fulltext}: \_\_j\ \_ja\ jac\ ack\ ck\_\ k\_\_\ \_\_m\ \_ma\ mal\ ale\ le\_\ e\_\_\}$$

4.3.2 Partitioned indexes and an aggregate index

We have indexed the tuples from all datasets into a single Lucene index. The tuples are tokenized using the 3-gram tokenizer in order to support fuzzy string matching as described in Section **??**. This index will be referred to as the *aggregate index* since it contains all the tuples from 10 datasets in a single index. The aggregate index contains approximately 877,000 documents.

We also have an alternative way of indexing the tuples using Lucene. We partition the tuples based on which relation they belong to. Given that we have 10 datasets, we have created 10 individual indexes, each containing the tuples from their respective relation. We refer to the set of indexes as *partitioned indexes*. The number of documents in each partitioned index is the same as the number of tuples in each dataset, as shown in Table **??**.

With the two types of indexing schemes (partitioned vs aggregate indexing), we have many alternatives in evaluating a user query.

Aggregate index lookup: we can simply issue the user query against the aggregate index as it contains all the available tuples.

- Pro: This is the traditional approach. It requires the least system design. Only a single thread is needed for each user query.
- Con: As we have indicated previously and will show in our experimental evaluation, this approach suffers from a performance bottleneck resulting from high token hashing collision rate.

Parallel lookup of partitioned indexes: we can issue the query against all individual index in the partitioned index set. This will perform parallel index lookup using multiple concurrent threads.

- Pro: The result can be found quickly. The index with the *correct* tuple will contain much less documents compared to the aggregate index, and thus will respond with the search result faster. In fact, we argue that this is the optimal performance one can expect.
- Con: The concurrency will impose a higher CPU and disk IO demand as each user query will take up to n threads to process. In high traffic or low resource

scenarios, this may be prohibitively expensive.

Predictive sequential lookup of partitioned indexes: we advocate to perform single threaded access of the partitioned indexes. But rather than simple or random sequential scan of the index set, we utilize predictive neural networks to generate an optimized access pattern, as described in Section **??**.

- Pro: This method enjoys the advantage of both single-threaded index lookup and low disk latency due to the potential early hit in a smaller partitioned index. So we argue that the predictive lookup will yield high query performance and low resource usage.
- Con: This method requires a self-supervised neural network to perform the prediction.

4.4 Evaluation methodology

We evaluate five model architectures, including Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), 1D Convolution (Conv1D), Transformer and MLP-Mixer. We also exam how misspelled keywords affect the models' top-5 accuracies.

We use two metrics for model evaluation. The first metric is query processing time. We submit queries to partitioned indexes and the aggregate index, and record the response times as evaluation benchmark. More details are given in the subsection **??**.

The second metric is top-k accuracy. A model's prediction gives us the ordering of Lucene index access. If the Lucene index that a query belongs to is among the top-k of the model's prediction, we consider the prediction accurate. For example, for a query sampled from `ds02`, if the predicted access ordering is

```
idx_ds06, idx_ds10, idx_ds07, idx_ds05, idx_ds02, ...
```

we consider it an accurate top-5 prediction.

In the following subsections, we give more details about our training data, query workloads and experiments. We first describe how training data and query workloads are generated and tokenized in subsections **??** and **??**, respectively. After that, we describe our experiments in subsections starting from **??** to **??**.

4.4.1 Training data generation and tokenization

The raw datasets are in SAS7BDAT format, which is a binary database format. To make data processing easier for the downstream model training and evaluation, we convert all raw datasets to CSV files. Then we remove some unuseful attributes. For example, the labour force survey dataset contains the attribute *rec_num*, which indicates the record number in the file. This attribute is removed since it is not useful for our model training. After that the preprocessed CSV files are splitted into data for model training and data for model evaluation. Data for model evaluation are used to generate query workloads. More details about the query workloads generation will be presented in subsection **??**.

Our next step is to generate training datasets from data reserved for model training. We randomly sample tuples from each CSV file without replacement. Then we normalize the sampled tuples to lowercase and remove special characters from them, which gives us word-based training data. In addition, we also apply character-based 3-gram tokenization to normalized tuples. We use "_" as the special character for padding in our implementation. This results in 3-gram based training data. For example, given a raw tuple:

```
(2019,April,"Employed, at work",Nova Scotia,Other CMA or non-CMA,
45 to 49 years,,Female,Married,Above bachelor''s degree,
"Single jobholder")
```

the normalized tuple will be:

```
(2019,april,employed at work,nova scotia,other cma or non cma,
45 to 49 years,female,married,above bachelors degree,
single jobholder)
```

and the 3-gram tokenized tuple will be:

```
(__2 _20 201 019 19_ 9__,__a _ap apr pri ril il_ l__,__e _em emp mpl
plo loy oye yed ed_ d__ __a _at at_ t__ __w _wo wor ork rk_ k__,__n
_no nov ova va_ a__ __s _sc sco cot oti tia ia_ a__,__o _ot oth the
her er_ r__ __c _cm cma ma_ a__ __o _or or_ r__ __n _no non on_ n__
__c _cm cma ma_ a__,__4 _45 45_ 5__ __t _to to_ o__ __4 _49 49_ 9__
__y _ye yea ear ars rs_ s__,__f _fe fem ema mal ale le_ e__, __m _ma
mar arr rri rie ied ed_ d__,__a _ab abo bov ove ve_ e__ __b _ba bac
ach che hel elo lor ors rs_ s__ __d _de deg egr gre ree ee_ e__,__s
_si sin ing ngl gle le_ e__ __j _jo job obh bho hol old lde der er_
r__)
```

Since we evaluate our models using partial tuple queries, a natural question is whether training models using partial tuples will have any impact on models' performance. Therefore, besides training datasets containing full tuples, we also create datasets containing partial tuples with 75% and 50% of attributes. Since each dataset will have an additional 3-gram tokenzed version, we have total six sets of training datasets. Table **??** shows their vocabulary sizes. In addition, we use dataset names as labels, so there is no need to manually label training tuples.

	100% attrs.		**75% attrs.**		**50% attrs.**	
	word-based	3-gram based	word-based	3-gram based	word-based	3-gram based
vocabulary size	56,482	4,136	47,536	4,130	37,183	4,109

Table 4.5: Vocabulary size of six sets of training datasets.

Workload name	**Description**
workload A	5 randomly sampled attributes
workload B	3 randomly sampled attributes

Table 4.6: Query workload names and descriptions.

4.4.2 Query workload generation and tokenization

Query workloads are sets of partial tuples. We first randomly sample tuples from data reserved for model evaluation. Then we apply the same normalization process to them as we do to training datasets. After that we convert them to partial tuples by randomly sampling some attributes from them. We create different workloads by varying the number of attributes sampled. Table **??** shows two query workloads we used for model evaluation.

4.4.2.1 Converting partial tuples to Lucene queries for searching

We use Lucene's Query API to construct search queries from partial tuples. First we apply 3-gram tokenization to a partial tuple to get a list of tokens. Then we convert each token to a search term. After that we use the logical `OR` operator to combine all search terms to form a query. For example, given a partial tuple as the following:

```
no very easy no
```

by adding the character "_" for padding, the constructed query will be:

```
__n OR _no OR no_ OR o__ OR __v OR _ve OR ver OR ery OR ry_ OR y__ OR
__e OR _ea OR eas OR asy OR sy_ OR y__ OR __n OR _no OR no_ OR o__
```

4.5 Experiments and observations

In this section, we will enumerate over the experiments we conducted to evaluate our methodology. For each experiment, we will focus on the motivation, experimental setup, the observation and their respective conclusions.

4.5.1 Performance of aggregate vs optimal index lookup

Description:

Our first experiment tries to establish a baseline for the evaluation of our methodology using the query processing time. We measure three types of performance. The first is the optimal performance, which is achievable by parallel partitioned indexes lookup. The second is the performance of the aggregate index lookup. The last is the performance of sequential scan of all partitioned indexes. This will be the worst sequential scan if the predicted ordering of index access from our neural network classifiers puts the true partitioned index, i.e., the one contains the tuple, as the last one to scan.

To create the performance benchmark, we perform search against partitioned indexes and the aggregate index using the constructed partial tuple queries and log the response times. We repeat the process 10 times and compute the mean response times to be used as benchmark for model evaluation. Table **??** and **??** show the mean response times in milliseconds (ms) of the first 20 queries of the workload A and B, respectively. Both of the workloads have 1,000 queries. In both tables, the first 10 columns are the results of partitioned indexes, and the last one is that of the aggregate index. Details about the query workloads are described in subsection **??**.

Observations:

As shown in figures **??** and **??**, the mean values of processing times of the worst

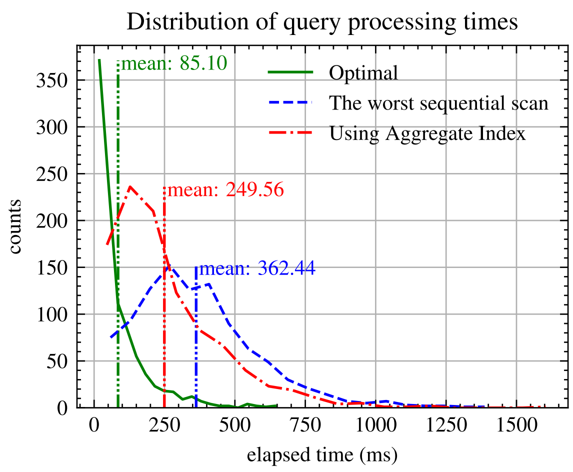
	idx_ds01	**idx_ds02**	**idx_ds03**	**idx_ds04**	**idx_ds05**	**idx_ds06**	**idx_ds07**	**idx_ds08**	**idx_ds09**	**idx_ds10**	**idx_agg**
0	46.57	18.074	11.766	12.315	11.681	10.991	8.146	32.037	42.178	12.506	171.814
1	9.785	95.191	9.112	3.577	5.211	5.076	42.509	25.545	11.406	8.152	34.883
2	41.464	30.662	15.134	7.381	9.833	6.114	16.265	25.711	130.263	28.414	340.52
3	81.665	71.147	10.45	11.374	13.238	62.585	24.985	33.262	89.623	22.483	214.195
4	11.86	12.193	4.124	3.576	2.569	4.466	5.933	14.683	10.914	7.414	27.807
5	111.691	35.233	23.712	14.259	37.553	32.163	90.013	38.077	64.649	56.575	410.775
6	10.171	15.061	6.72	6.757	5.178	6.366	20.423	9.027	17.965	13.738	48.165
7	8.565	17.936	3.222	11.276	3.91	9.101	12.828	8.33	29.897	50.721	113.489
8	4.702	2.492	3.492	2.109	1.748	2.76	1.972	10.48	6.715	5.909	18.459
9	29.805	25.247	4.121	3.972	3.618	8.858	21.882	65.882	40.683	97.196	403.81
10	12.438	28.071	11.567	7.722	8.266	8.296	17.631	25.093	28.216	30.15	69.155
11	78.894	199.486	36.34	16.409	59.3	19.544	52.956	31.944	81.945	49.079	269.655
12	34.995	17.869	6.531	8.366	4.515	9.189	11.174	38.777	33.707	16.754	98.553
13	27.613	291.843	36.575	18.002	16.23	21.494	10.564	35.939	35.287	9.281	513.177
14	14.984	19.801	18.374	7.259	9.394	10.142	11.601	10.555	24.247	5.859	181.814
15	13.587	7.268	3.283	4.145	2.499	3.895	11.989	9.273	72.258	10.647	210.635
16	13.702	95.056	9.045	3.973	5.103	8.488	38.507	36.359	12.235	17.131	49.995
17	56.258	33.413	15.297	20.917	77.721	36.136	20.222	23.676	60.217	25.79	200.614
18	82.657	47.663	13.094	16.612	20.459	22.733	250.602	23.769	66.409	15.952	349.091
19	54.616	101.808	19.846	10.232	17.782	10.651	15.67	20.257	31.221	18.2	170.922

Table 4.7: Mean query processing time in milliseconds of the query workload A.

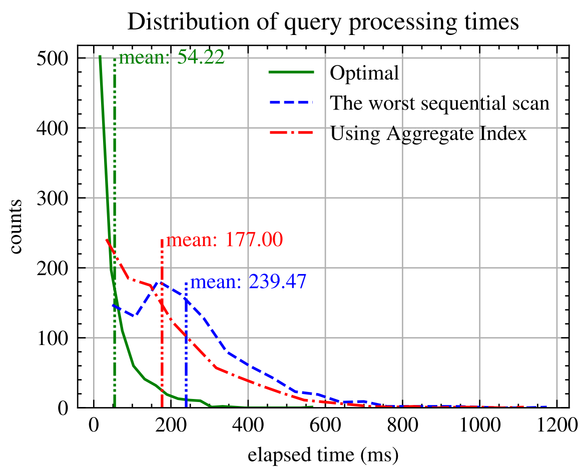
	idx_ds01	**idx_ds02**	**idx_ds03**	**idx_ds04**	**idx_ds05**	**idx_ds06**	**idx_ds07**	**idx_ds08**	**idx_ds09**	**idx_ds10**	**idx_agg**
0	98.113	57.467	10.403	37.902	12.051	62.483	38.51	26.149	165.856	16.691	314.936
1	14.557	55.388	28.667	5.697	9.935	7.249	11.154	12.134	71.949	8.198	238.055
2	8.631	3.937	3.175	2.545	5.582	2.101	9.151	4.998	15.669	4.413	67.788
3	11.335	102.476	9.366	3.973	5.219	5.831	43.672	31.271	11.799	10.532	38.502
4	5.308	3.488	1.841	1.794	1.599	1.831	2.318	5.721	5.43	4.208	16.736
5	3.67	3.528	1.455	0.888	1.378	1.309	1.754	3.788	5.68	5.098	7.443
6	91.594	71.66	13.706	19.588	13.286	26.387	19.932	34.864	100.266	149.223	534.203
7	31.022	8.103	3.399	3.869	10.046	19.07	24.614	21.792	12.224	21.41	79.365
8	12.886	2.355	1.921	1.164	1.289	1.857	2.255	21.522	13.225	8.419	57.589
9	22.284	24.1	5.037	5.806	5.746	6.755	29.814	47.61	18.798	95.213	123.481
10	15.28	100.405	18.486	22.014	10.342	14.922	23.115	46.89	71.578	44.932	257.194
11	25.516	112.658	16.634	7.536	10.233	3.534	10.162	23.997	23.325	17.062	208.747
12	10.205	14.475	2.911	8.536	14.028	10.525	28.727	13.78	13.006	6.637	144.816
13	22.995	37.862	31.601	5.188	6.149	12.015	13.627	12.671	37.18	7.093	263.558
14	19.333	17.295	22.824	9.389	7.053	8.066	14.066	14.804	28.168	12.026	143.885
15	19.342	15.851	17.527	8.61	10.577	10.279	6.839	13.137	94.481	5.259	151.432
16	14.672	6.689	3.557	3.29	5.204	5.284	8.676	4.322	17.68	4.766	98.075
17	37.963	110.194	27.724	24.375	57.606	39.03	10.182	58.863	56.036	16.456	235.116
18	53.005	31.016	6.474	14.265	10.915	30.343	160.273	9.875	18.179	11.012	263.5
19	8.122	40.389	4.695	2.191	19.547	7.517	8.134	6.303	25.256	9.781	56.903

Table 4.8: Mean query processing time in milliseconds of the query workload B.

sequential scan are longer than that of searching the aggregate index. The worst sequential scan is slower than searching the aggregate index by 45% and 35%, respectively. The goal of our neural network classifiers is to improve the performance of sequential scan by generating an optimized access pattern.



(a) Workload A



(b) Workload B

Figure 4.2: The distribution of query processing times of workload A and B.

4.5.2 Performance of optimal matching for partial tuple completion

In this experiment, we examine the performance of optimal matching in three different steps. In our first step, we set query size to be 10, tuple size to be 200, and edge connectivity density to be 0.1. We compute the optimal matching for 100 times and record the response times. Figure **??** shows the histogram of the results. In our second step, we vary edge connectivity densities with the same fixed query size and tuple size as in step one. We repeat the process 100 times and compute the mean response times as results, which are shown in Figure **??**. In our last step, we fix the query size and edge connectivity density to be the same as in step one, but change the tuple size so that it goes from 100 to 1,000. Again, we repeat the process for 100 times and compute the mean values. Figure **??** shows the results.

Our workloads A and B have query sizes of 3 and 5, respectively. The average number of attributes of the 10 datasets is less than 200. The experiment results from the above three steps indicate that the response time of optimal matching will be less

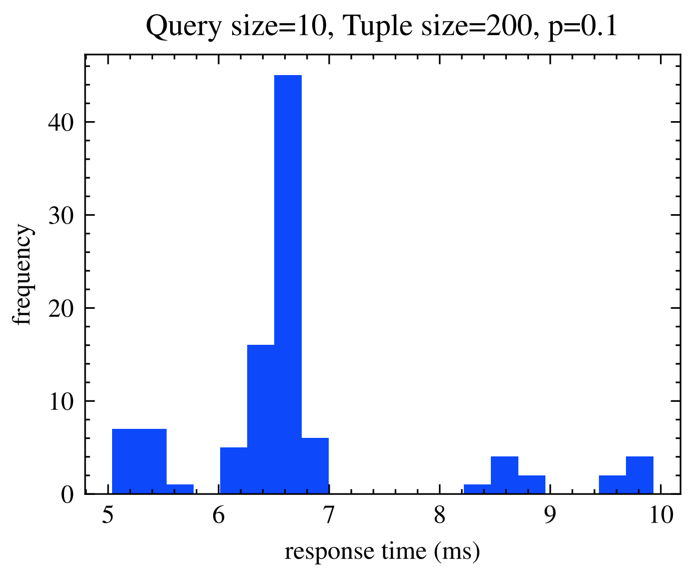


Figure 4.3: Distribution of optimal matching response times (ms)

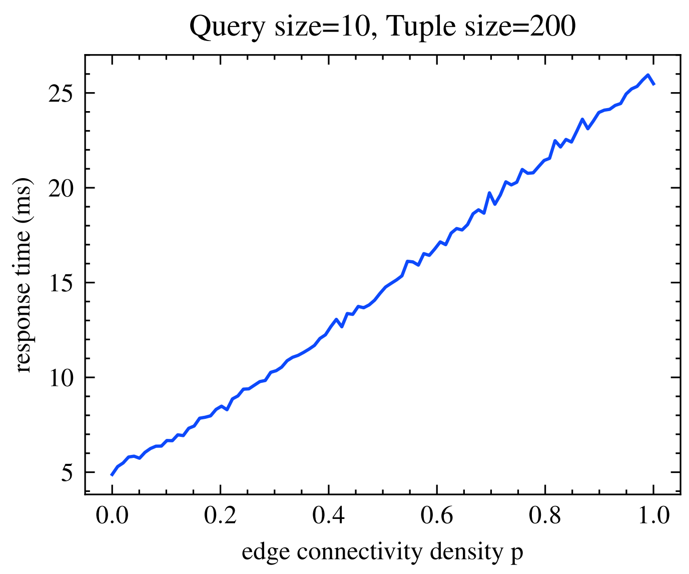


Figure 4.4: Optimal matching response time (ms) w.r.t. varying edge connectivity densities

than 30 milliseconds in our use case. The performance cost of optimal matching will not be as significant as that of full-text index lookup. Therefore, the majority of our work focuses on how to optimize index lookup using neural networks.

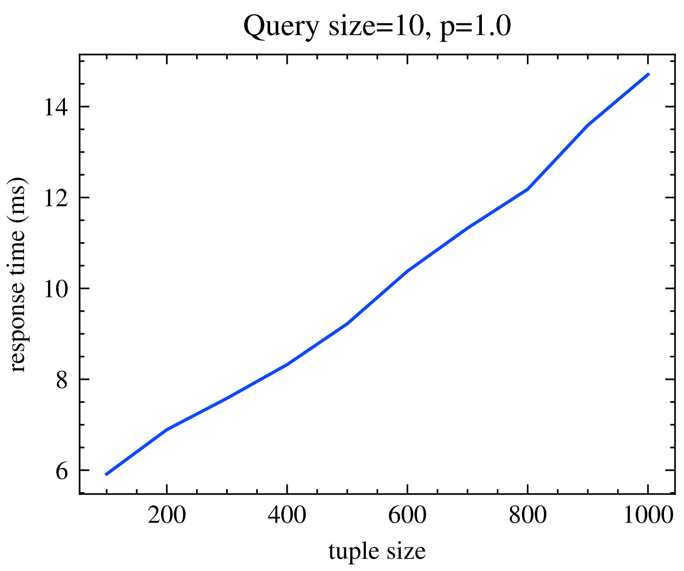


Figure 4.5: Optimal matching response time (ms) w.r.t. varying tuple sizes

4.5.3 Neural network based predictive access

We evaluate five neural network architectures including MLP, LSTM, Conv1D, Transformer and MLP-Mixer. While all of them can be made into deep networks, or in conjunction with other network architectures, our motivation is to make our models as small as possible so that they can be embedded in a search system. Therefore, we focus on the minimalist approach to network design.

4.5.3.1 Common experimental setup and evaluation metrics

Evaluation scenarios: We evaluate models with the following combination of different scenarios in all experiments:

- We train the models using different sampling rates of attributes, as described in Section **??**.
- We consider both word-based and 3-gram based training.

- We evaluate the performance of index scan using models' predictions and compare with the optimal and aggregate index lookup for each query in our query workloads.

Tokenization and embedding of texts: The tokens are either words or 3-grams of the values in the partial tuples. Let **Voc** be the vocabulary. The vocabulary size is determined by the attribute sampling rate during training. The vocabulary sizes are given in Table **??**. Each token is embedded into $\mathbb{R}^{64}$ by a simple embedding layer that has $|\mathbf{Voc}| \times 64$ parameters.

Evaluation metrics: We evaluate our models using the following metrics:

- Top-k classification accuracy: since we know the true relations that contain the partial tuples in our query workloads, we can evaluate the classification accuracy of our model. The top-k accuracy is defined as the percentage of the correct label among the top-k labels predicted.

- Index lookup response time using the predicted access pattern: using the likelihoods produced by our model, we can sort the indexes by their likelihoods and access the most likely index first. The scan continues until the true relation is reached.

4.5.3.2 Multilayer perceptron (MLP)

Description:

Multilayer perceptron (MLP) is probably the most widely used neural network architecture. In this experiment, we will test the effectiveness of MLP by itself with a single hidden layer.

Model architecture:

- Since each query is a sequence of tokens, each query is embedded into $\mathbb{R}^{L\times 64}$ where L is the token sequence length. We use global average pooling to generate a flat vector in $\mathbb{R}^{64}$, which is used as the input to the MLP layer.
- MLP has one hidden layer of size 100.
- We utilize one drop-out layer to prevent overfitting by the large embedding layer.

The overall network architecture can be found in Figure **??**. Since we have six

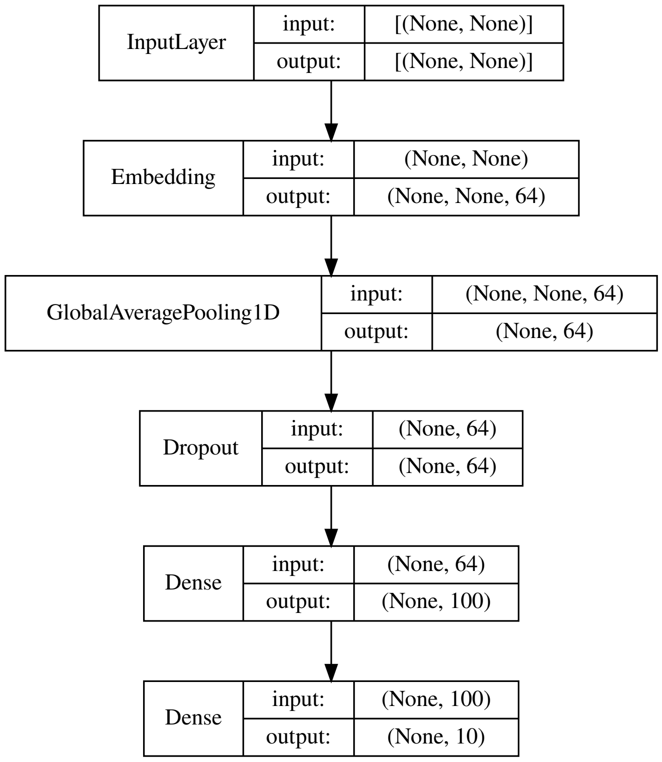


Figure 4.6: MLP model

sets of training datasets, we have 6 trained MLP models, as shown in Table **??**.

Observations:

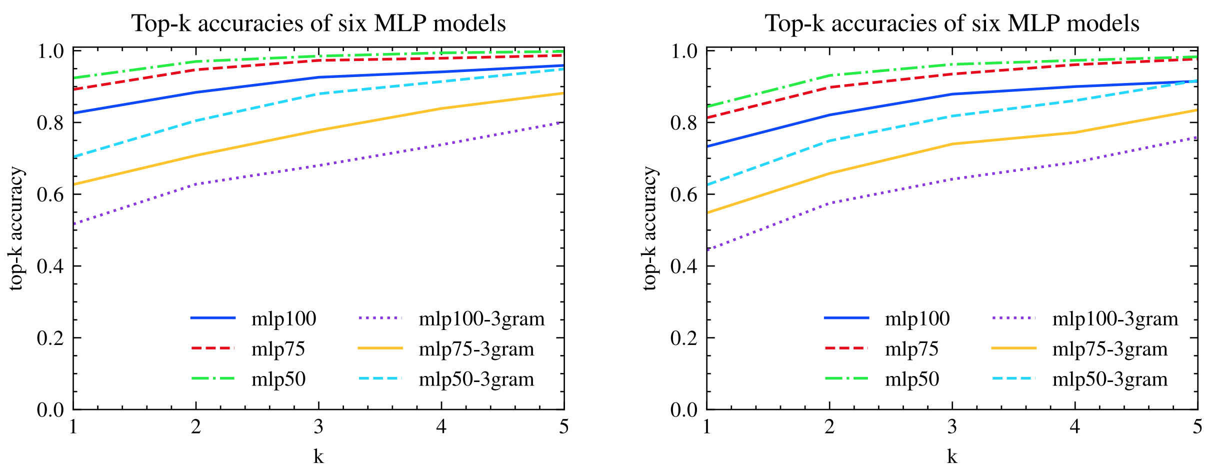
- The top-1 to top-5 accuracies for all variations of MLP models under the workloads A and B are shown in Figure **??**. Word-based models perform better than

Model name	**Training dataset**
mlp100	100% attrs., word-based
mlp100-3gram	100% attrs., 3-gram based
mlp75	75% attrs., word-based
mlp75-3gram	75% attrs., 3-gram based
mlp50	50% attrs., word-based
mlp50-3gram	50% attrs., 3-gram based

Table 4.9: MLP model names and corresponding training datasets.

3-gram based models under both workloads, which do not contain misspelled and unknown keywords.

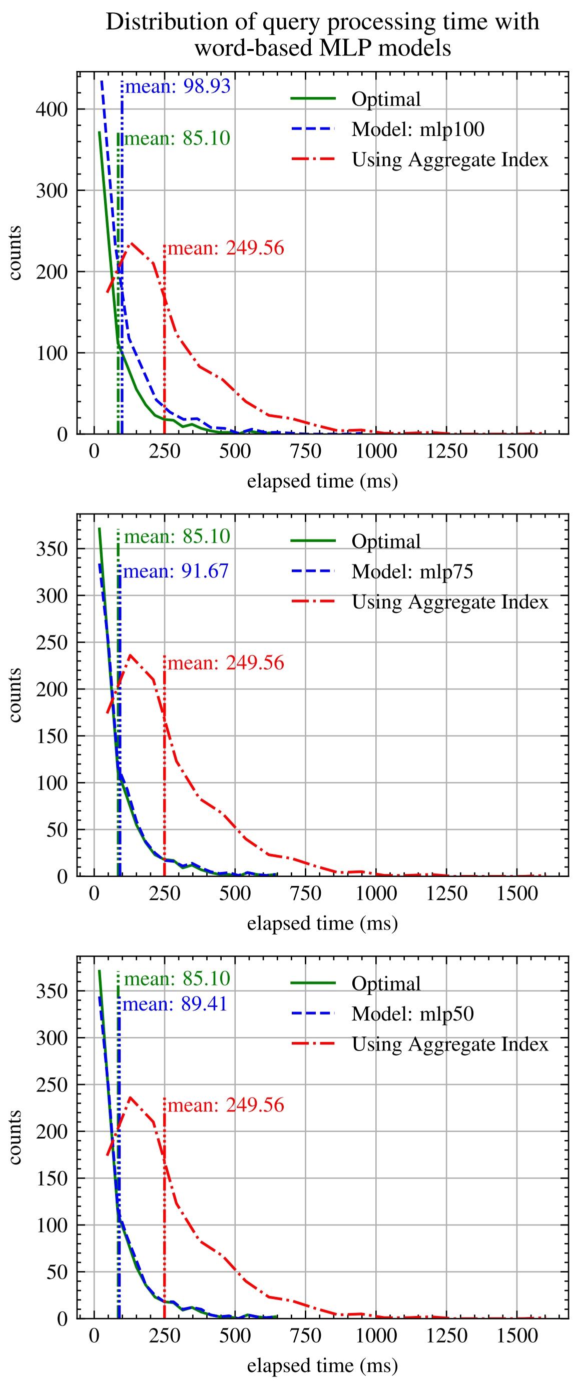
- Figure **??** and Figure **??** show the distribution of query processing time under the workloads A and B, respectively. Word-based models improve query processing more than 3-gram based models do. In addition, the models trained using partial tuples with less attributes perform better than those trained using partial tuples with more attributes.



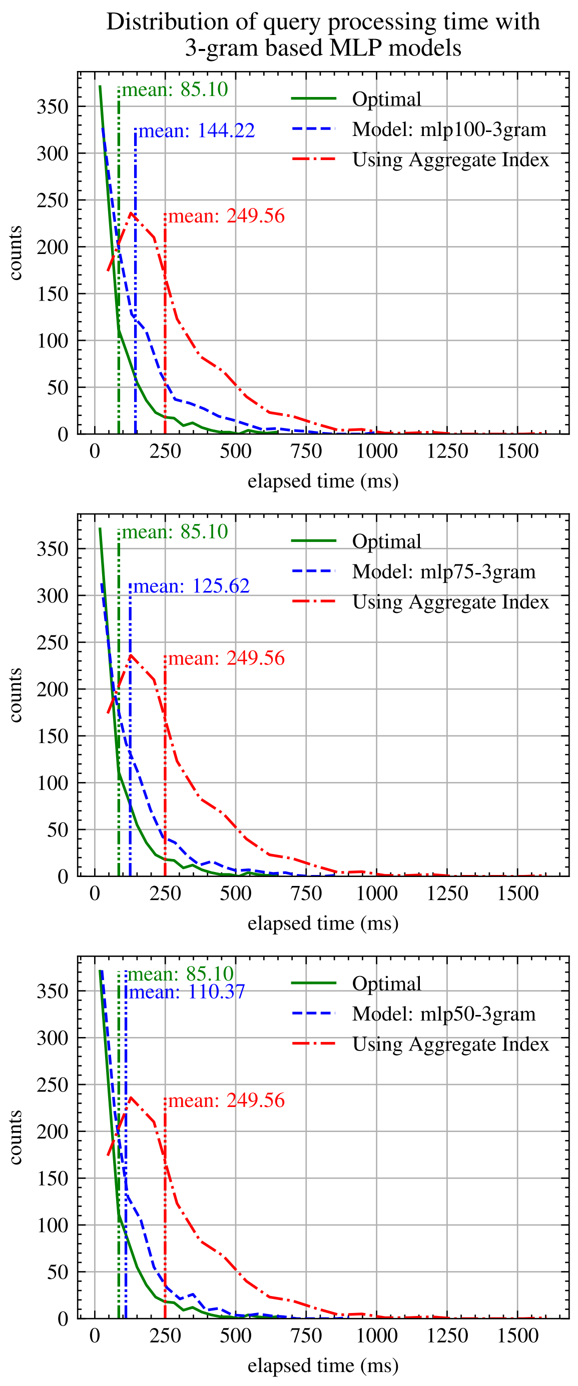
(a) Under the workload A.

(b) Under the workload B.

Figure 4.7: Top-k accuracies of six MLP models under the workload A and B.

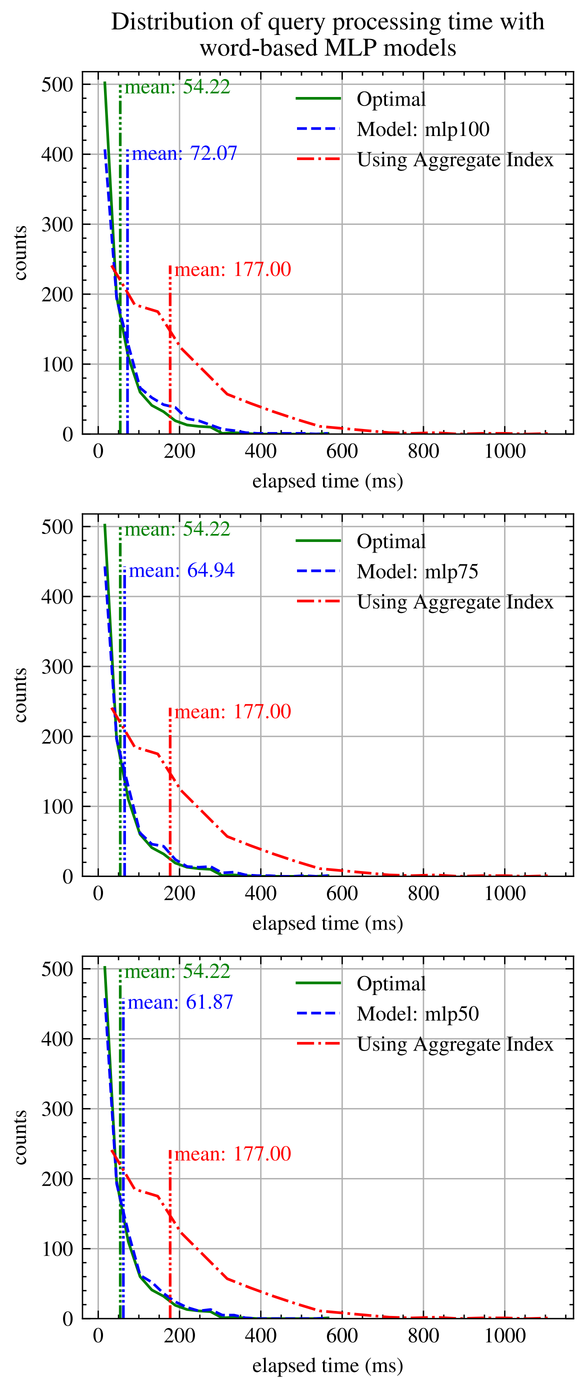


(a) Word-based MLP models

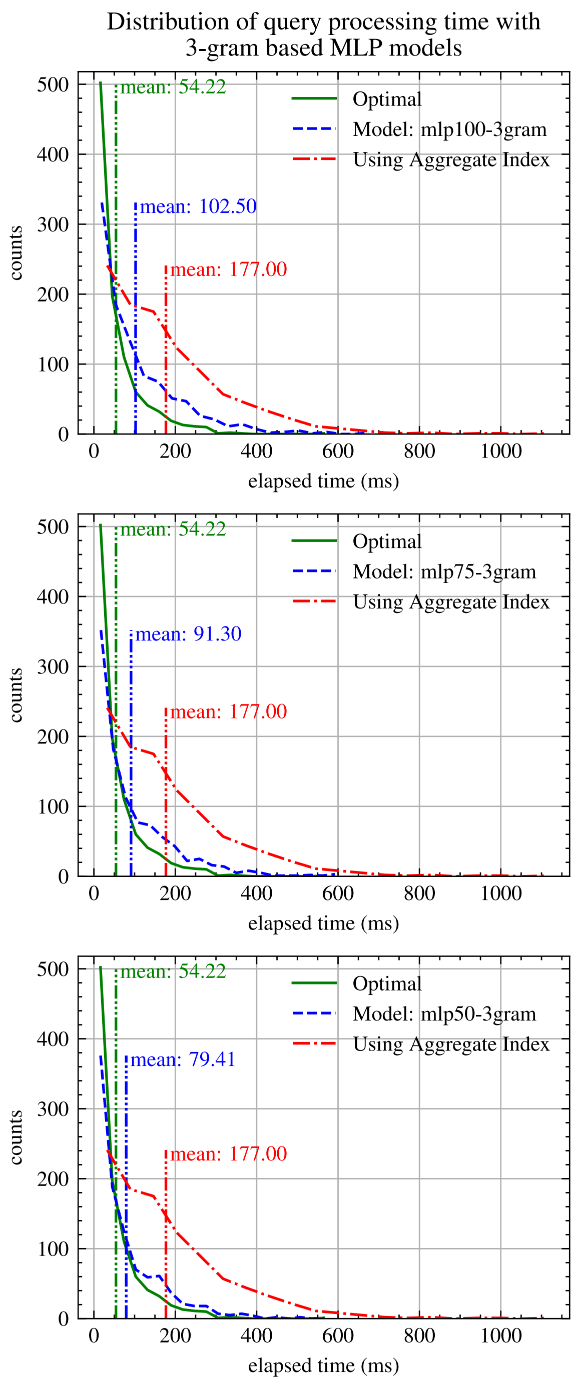


(b) 3-gram based MLP models

Figure 4.8: Distribution of query processing time with MLP models under the workload A.



(a) Word-based MLP models



(b) 3-gram based MLP models

Figure 4.9: Distribution of query processing time with MLP models under the workload B.

4.5.3.3 Long short-term memory (LSTM)

*D*escription:

Long short-term memory (LSTM) is a neural network architecture for sequence learning. Even though attributes in a tuple is not considered as a sequence since they are not ordered, the attribute values can be considered as short sequences of tokens. We test how LSTM performs when dealing with relational data in this experiment. Again we apply the minimalist approach to its network design by a single LSTM layer.

Model architecture:

- Each query is embedded into $\mathbb{R}^{L\times 64}$ where L is the token sequence length, which is used as the input to the LSTM layer.
- We apply one drop-out layer to the output of the LSTM layer to prevent overfitting.
- The LSTM model has one hidden layer of size 100.

The model architecture is shown in Figure **??**. The 6 trained LSTM models are listed in Table **??**.

Model name	**Training dataset**
lstm100	100% attrs., word-based
lstm100-3gram	100% attrs., 3-gram based
lstm75	75% attrs., word-based
lstm75-3gram	75% attrs., 3-gram based
lstm50	50% attrs., word-based
lstm50-3gram	50% attrs., 3-gram based

Table 4.10: LSTM model names and corresponding training datasets.

*O*bservations:

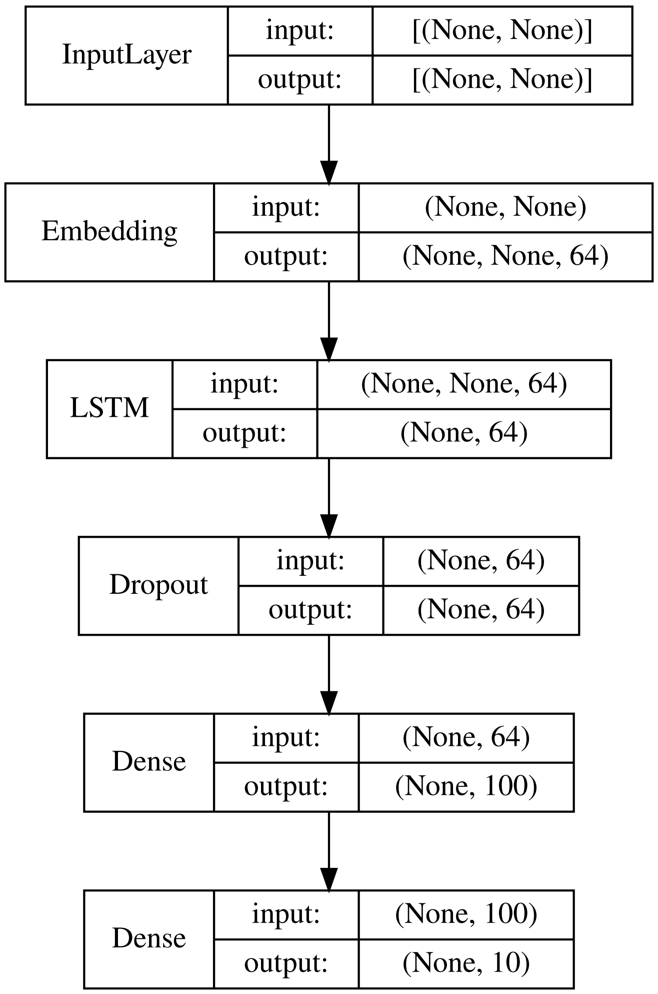
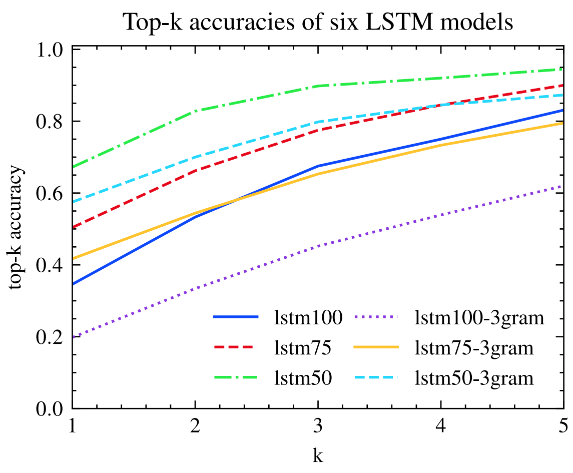


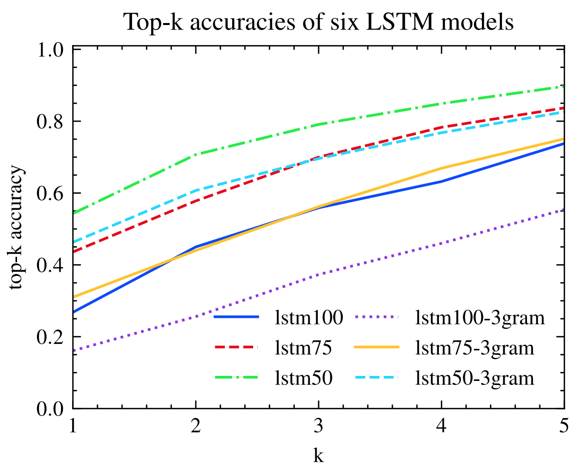
Figure 4.10: LSTM model

- The top-1 to top-5 accuracies for all variations of LSTM models under the workloads A and B are shown in Figure **??**. Word-based models perform better than 3-gram based models. When compared to MLP models, LSTM models underperform under both workloads.

- Figure **??** and Figure **??** show the distribution of query processing time under the workloads A and B, respectively. Word-based models improve query processing more than 3-gram based models do. In addition, similar to MLP models, the models trained using partial tuples with less attributes perform better than those trained using partial tuples with more attributes.



(a) Under the workload A.



(b) Under the workload B.

Figure 4.11: Top-k accuracies of six LSTM models under the workload A and B.

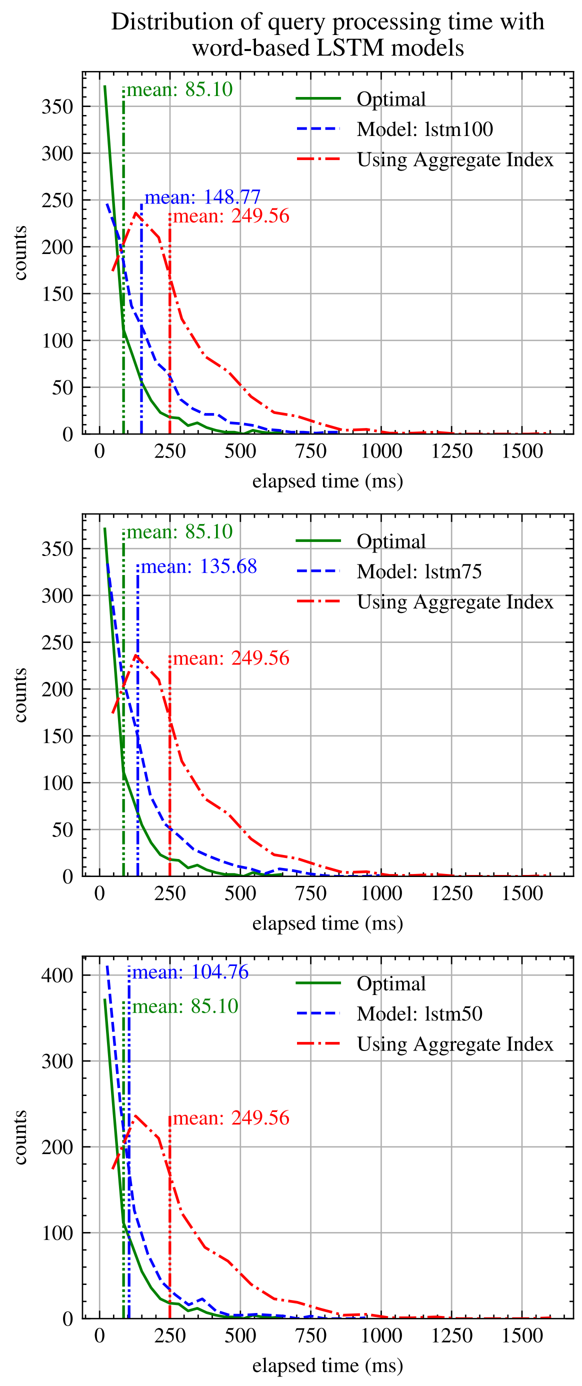
4.5.3.4 One dimensional convolution (Conv1D)

*D*escription:

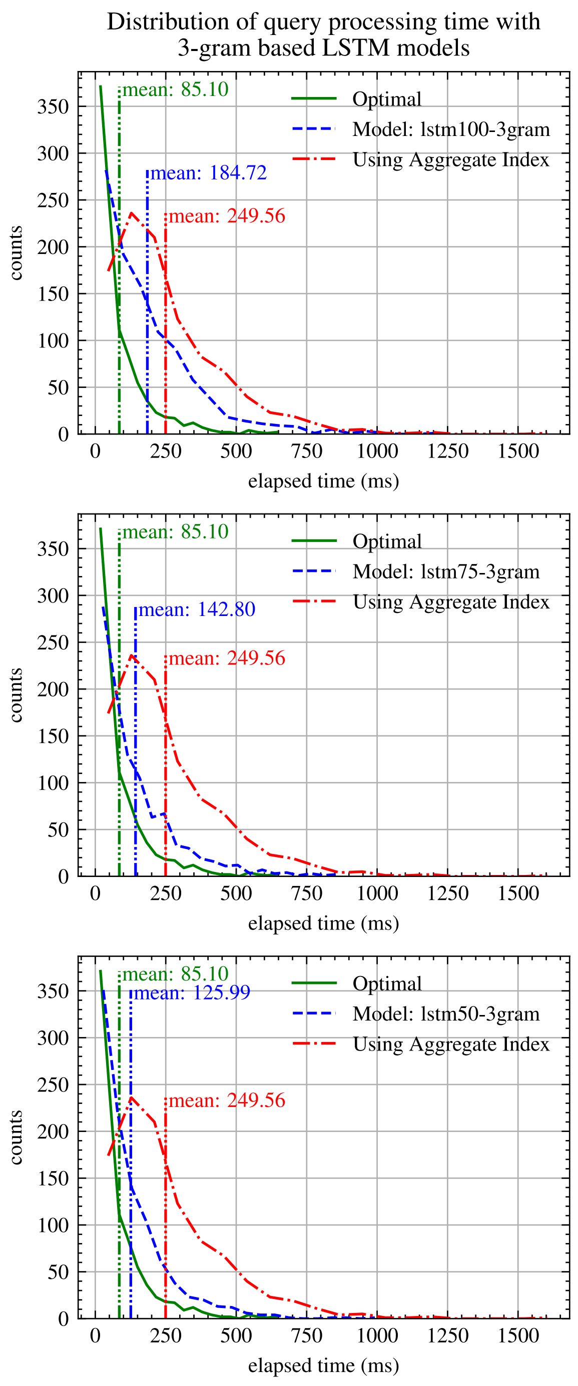
Another way of doing sequence learning is 1-dimensional convolutional neural networks (Conv1D). Similar to what we do to LSTM, we want to see how Conv1D performs when processing relational data. We also minimize the network structure by using a single Conv1D layer.

Model architecture:

- Each query is embedded into $\mathbb{R}^{L\times 64}$ where L is the token sequence length, which is used as the input to the Conv1D layer.
- The Conv1D layer has 64 kernels with kernel size of 3.
- We apply global average pooling to the output of Conv1D layer to generate a flat vector in $\mathbb{R}^{64}$.

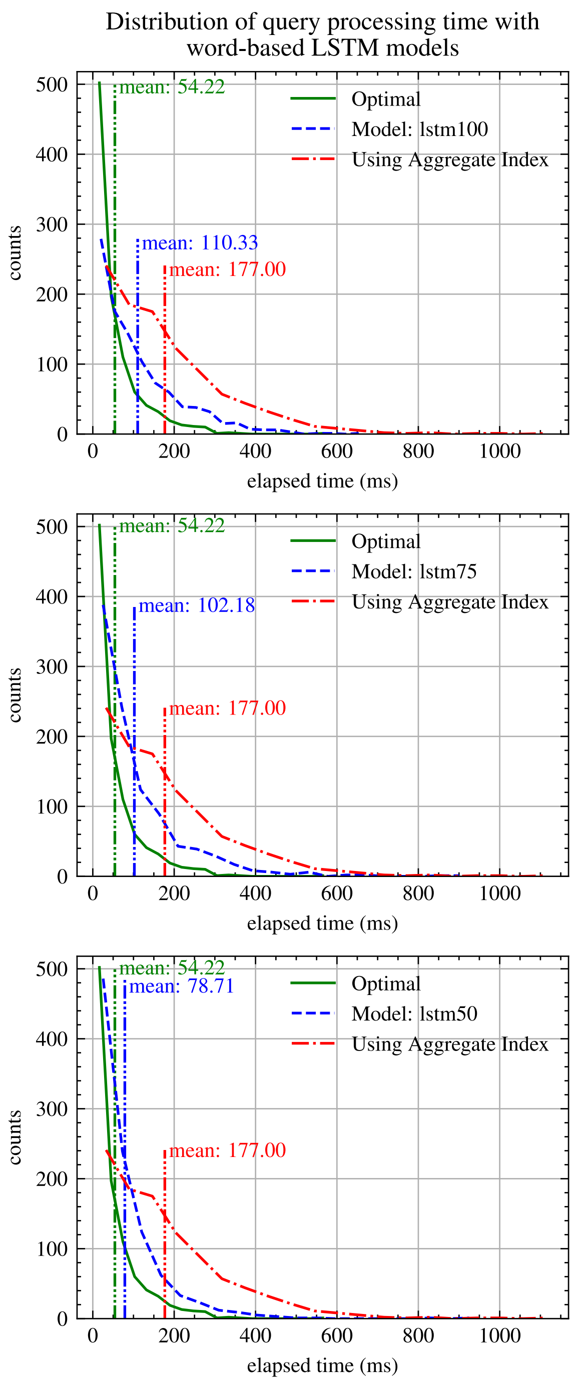


(a) Word-based LSTM models

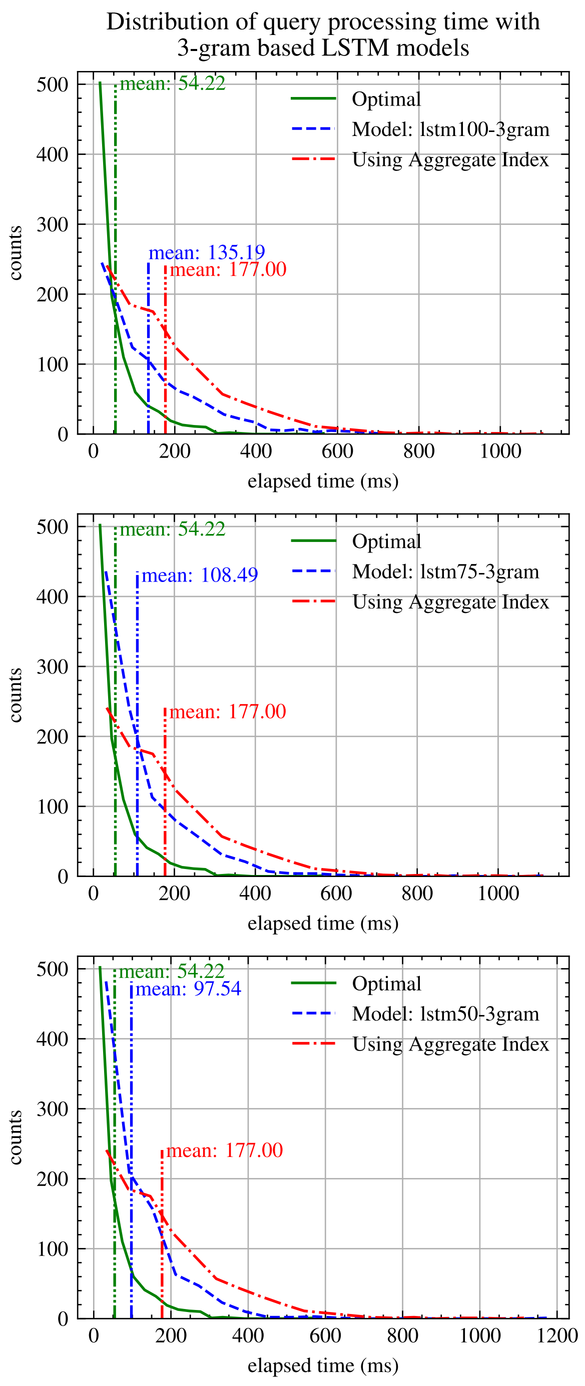


(b) 3-gram based LSTM models

Figure 4.12: Distribution of query processing time with LSTM models under the workload A.



(a) Word-based LSTM models



(b) 3-gram based LSTM models

Figure 4.13: Distribution of query processing time with LSTM models under the workload B.

- We apply one drop-out layer to the flattened vector to prevent overfitting.

The model architecture is shown in Figure **??**. The 6 trained Conv1D models are listed in Table **??**.

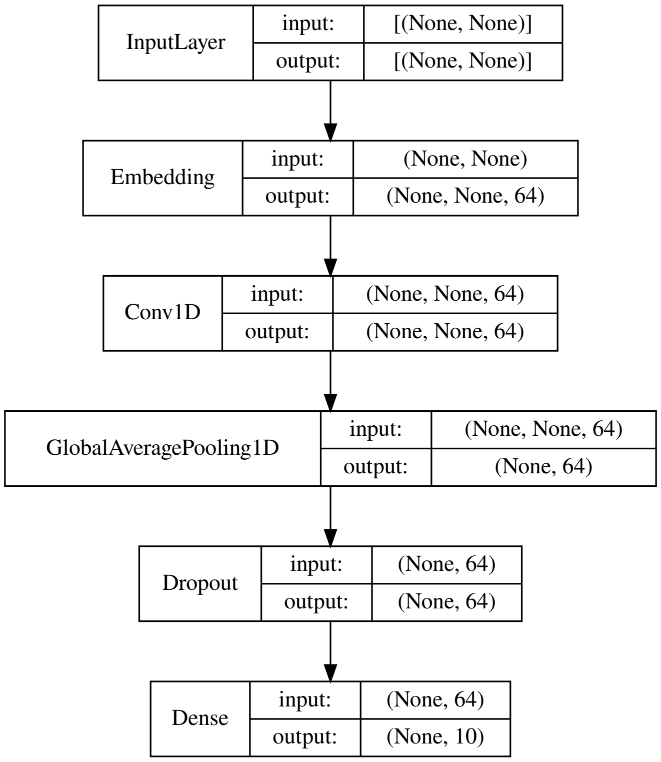


Figure 4.14: Conv1D model

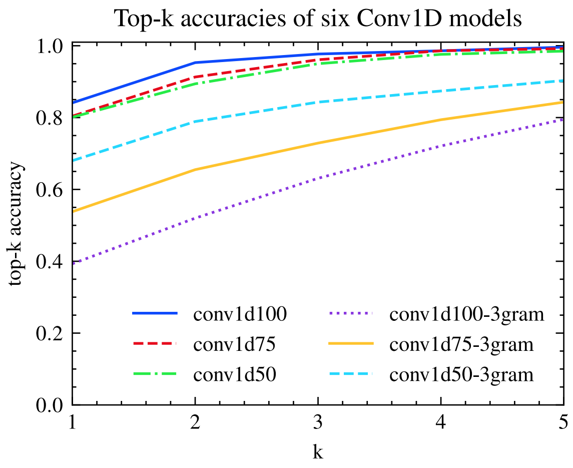
Model name	**Training dataset**
conv1d100	100% attrs., word-based
conv1d100-3gram	100% attrs., 3-gram based
conv1d75	75% attrs., word-based
conv1d75-3gram	75% attrs., 3-gram based
conv1d50	50% attrs., word-based
conv1d50-3gram	50% attrs., 3-gram based

Table 4.11: Conv1D model names and corresponding training datasets.

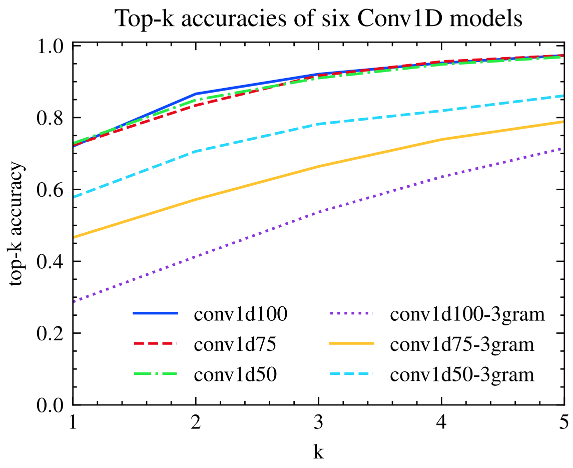
Observations:

- The top-1 to top-5 accuracies for all variations of Conv1D models under the workloads A and B are shown in Figure **??**. Word-based models perform better than 3-gram based models.

- Figure **??** and Figure **??** show the distribution of query processing time under the workloads A and B, respectively. Word-based models improve query processing more than 3-gram based models do. Under the workload A, the 3-gram based models trained using partial tuples with less attributes perform better than those trained using partial tuples with more attributes, but the word-based models show an opposite relationship. Under the workload B, both word-based and 3-gram based models do better when trained using partial tuples with less attributes.



(a) Under the workload A.

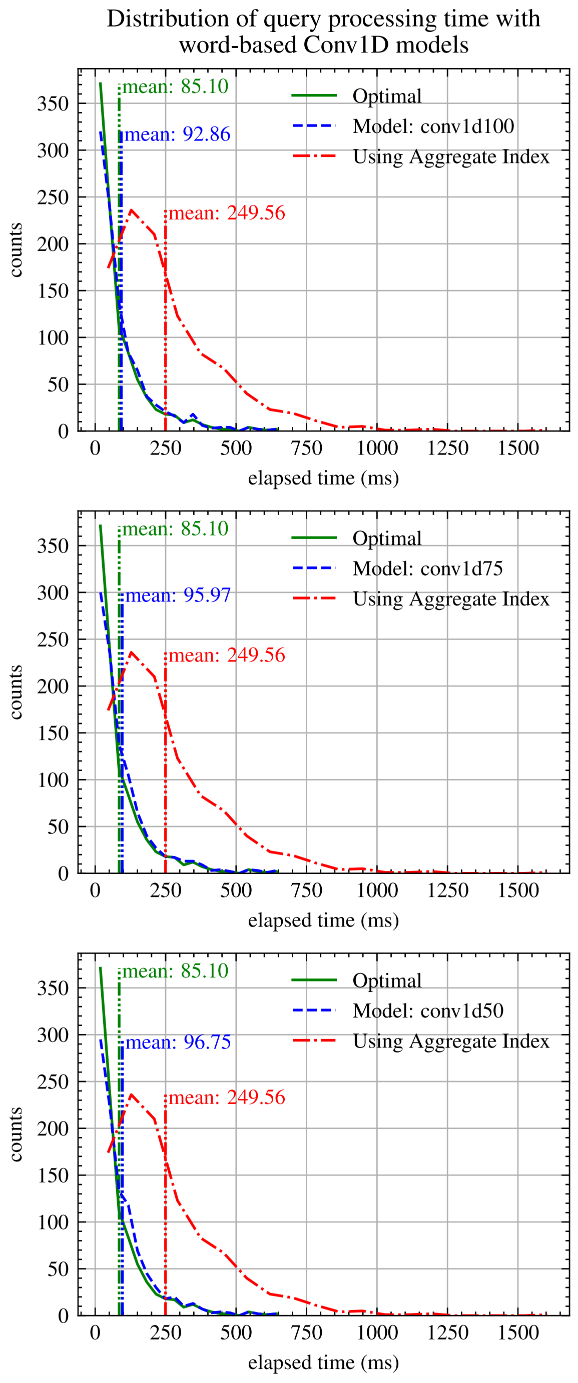


(b) Under the workload B.

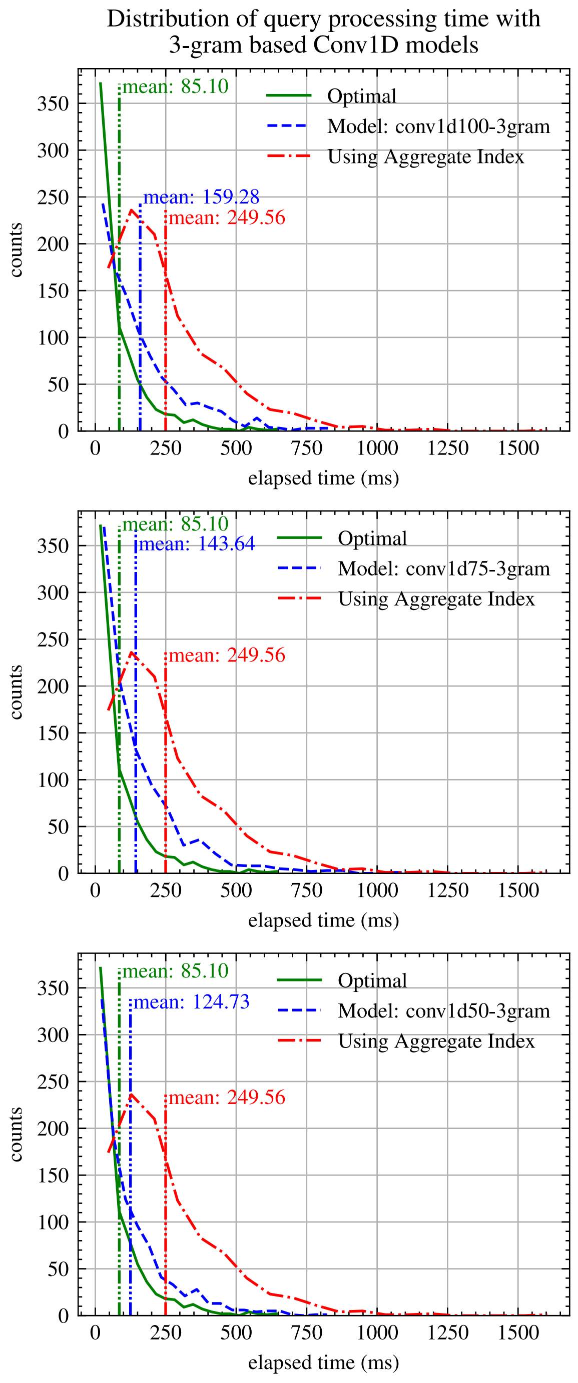
Figure 4.15: Top-k accuracies of six Conv1D models under the workload A and B.

4.5.3.5 Single transformer block

*D*escription:

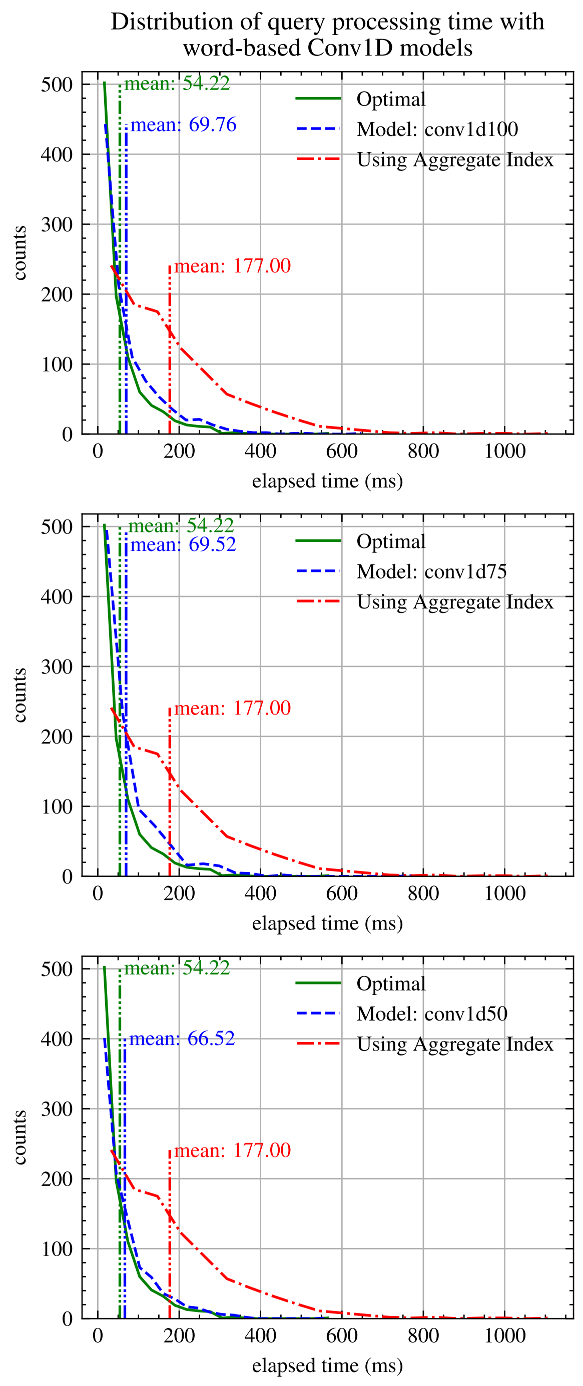


(a) Word-based Conv1D models

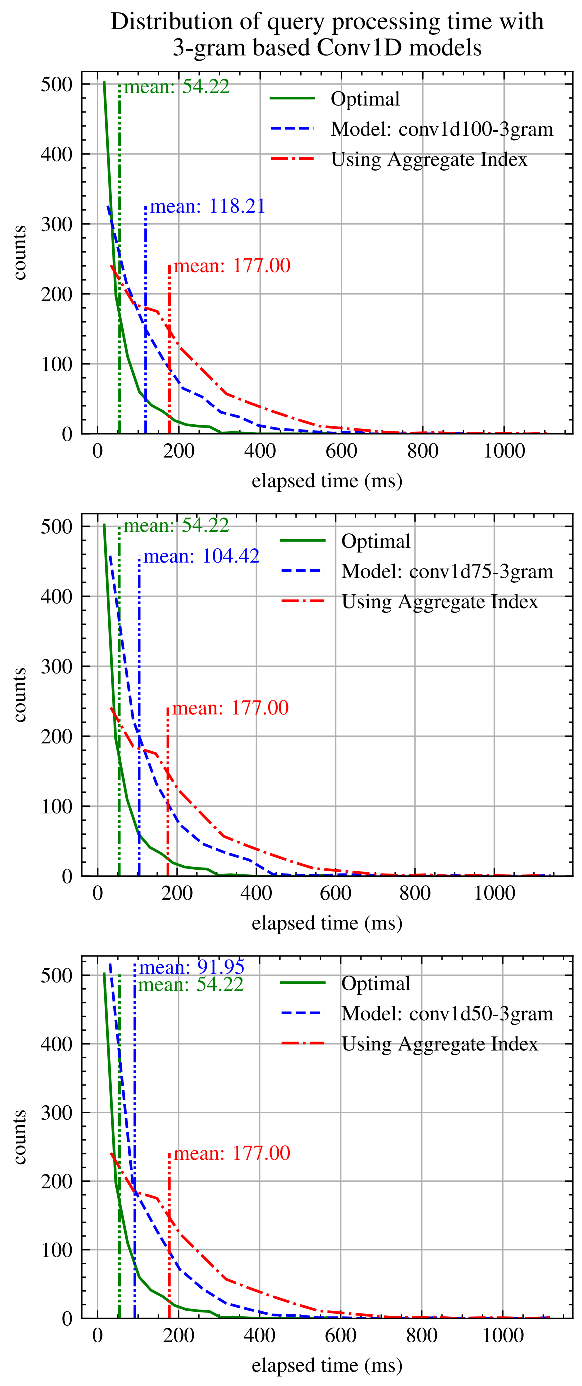


(b) 3-gram based Conv1D models

Figure 4.16: Distribution of query processing time with Conv1D models under the workload A.



(a) Word-based Conv1D models



(b) 3-gram based Conv1D models

Figure 4.17: Distribution of query processing time with Conv1D models under the workload B.

The Transformer architecture introduced in the original Transformer paper [**DBLP:journals/corr/Vas**
is one of the main advances in natural language processing. In this experiment, we evaluate Transformer architecture for relational data. We largely follow the encoder architecture of the vanilla Transformer presented in the paper [**DBLP:journals/corr/VaswaniSPUJGK**
However, since our data are relational, we remove positional encoding. In addition, we only create one Transformer block to minimize the model architecture.

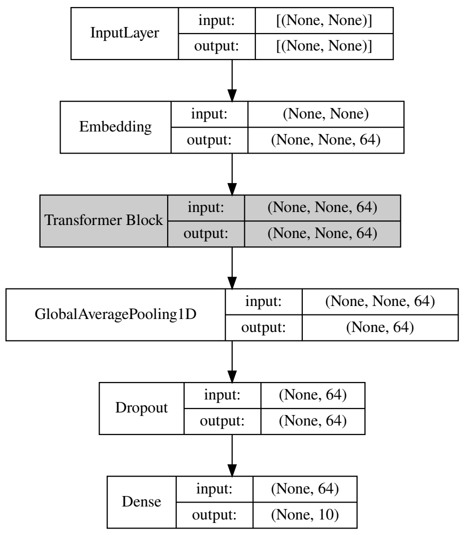
Model architecture:

- Each query is embedded into $\mathbb{R}^{L\times 64}$ where L is the token sequence length, which is used as the input to the Transformer block.
- Inside the Transformer block, the attention layer has 4 attention heads. We add an extra drop-out layer after both the attention layer and the feed-forward network to prevent overfitting.
- The feed-forward network has a hidden layer of size 64.
- We apply global average pooling to the output of the Transformer block to generate a flat vector in $\mathbb{R}^{64}$.
- Then we apply a drop-out layer to the flattened vector.

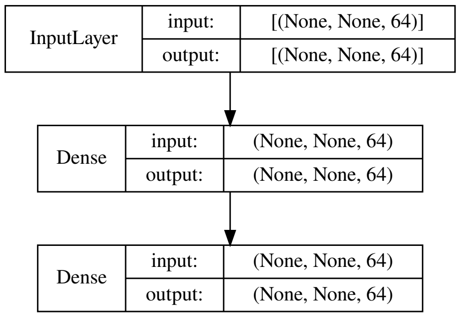
Figure **??** shows its architecture. The 6 trained Transformer models are listed in Table **??**.

*O*bservations:

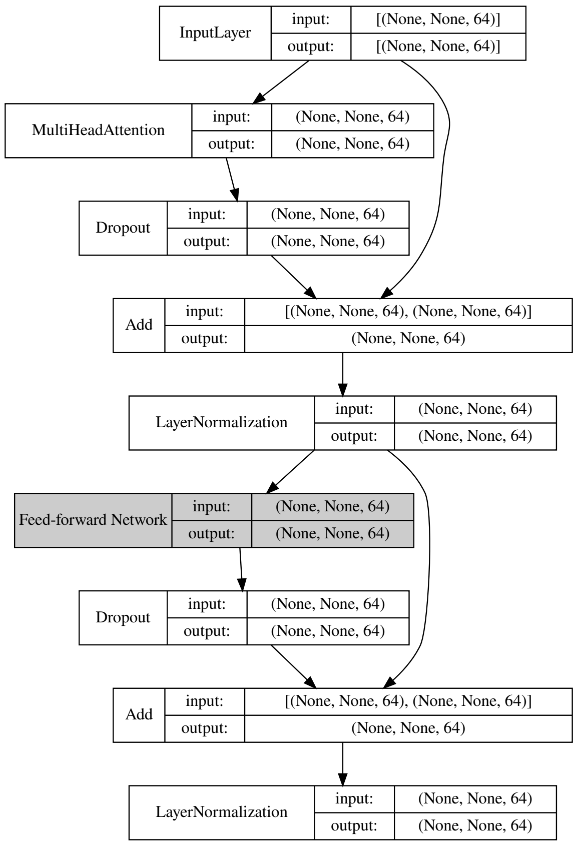
- The top-1 to top-5 accuracies for all variations of Transformer models under the workloads A and B are shown in Figure **??**. Again, word-based models perform better than 3-gram based models.


InputLayer input: [(None, None)] output: [(None, None)]
Embedding input: (None, None) output: (None, None, 64)
Transformer Block input: (None, None, 64) output: (None, None, 64)
GlobalAveragePooling1D input: (None, None, 64) output: (None, 64)
Dropout input: (None, 64) output: (None, 64)
Dense input: (None, 64) output: (None, 10)

(a) Overall architecture


InputLayer input: [(None, None, 64)] output: [(None, None, 64)]
Dense input: (None, None, 64) output: (None, None, 64)
Dense input: (None, None, 64) output: (None, None, 64)

(b) Feed-forward network


InputLayer input: [(None, None, 64)] output: [(None, None, 64)]
MultiHeadAttention input: (None, None, 64) output: (None, None, 64)
Dropout input: (None, None, 64) output: (None, None, 64)
Add input: [(None, None, 64), (None, None, 64)] output: (None, None, 64)
LayerNormalization input: (None, None, 64) output: (None, None, 64)
Feed-forward Network input: (None, None, 64) output: (None, None, 64)
Dropout input: (None, None, 64) output: (None, None, 64)
Add input: [(None, None, 64), (None, None, 64)] output: (None, None, 64)
LayerNormalization input: (None, None, 64) output: (None, None, 64)

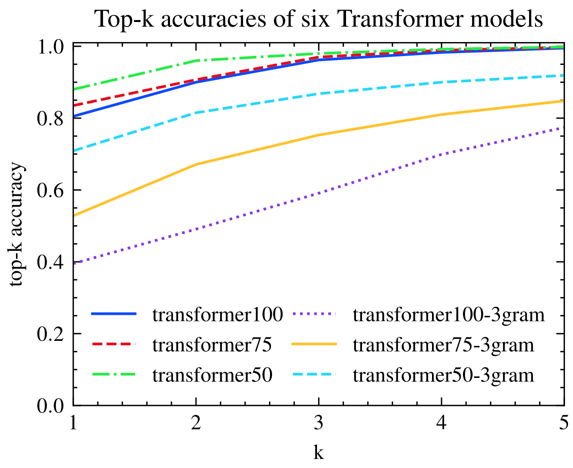
(c) Transformer block

Figure 4.18: Transformer model

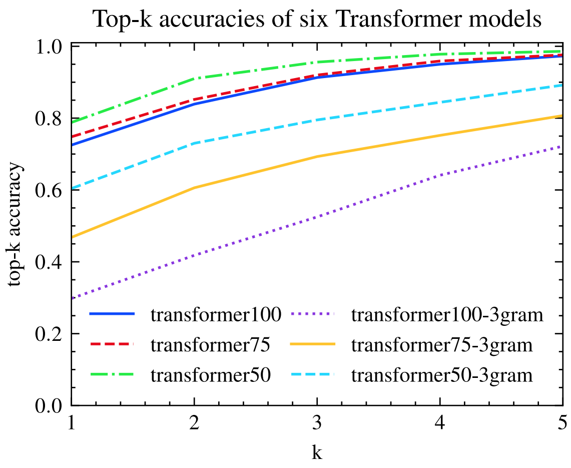
Model name	**Training dataset**
transformer100	100% attrs., word-based
transformer100-3gram	100% attrs., 3-gram based
transformer75	75% attrs., word-based
transformer75-3gram	75% attrs., 3-gram based
transformer50	50% attrs., word-based
transformer50-3gram	50% attrs., 3-gram based

Table 4.12: Transformer model names and corresponding training datasets.

- Figure **??** and Figure **??** show the distribution of query processing time under the workloads A and B, respectively. Word-based models improve query processing more than 3-gram based models do. In addition, the models trained using partial tuples with less attributes perform better than those trained using partial tuples with more attributes.



(a) Under the workload A.



(b) Under the workload B.

Figure 4.19: Top-k accuracies of six Transformer models under the workload A and B.

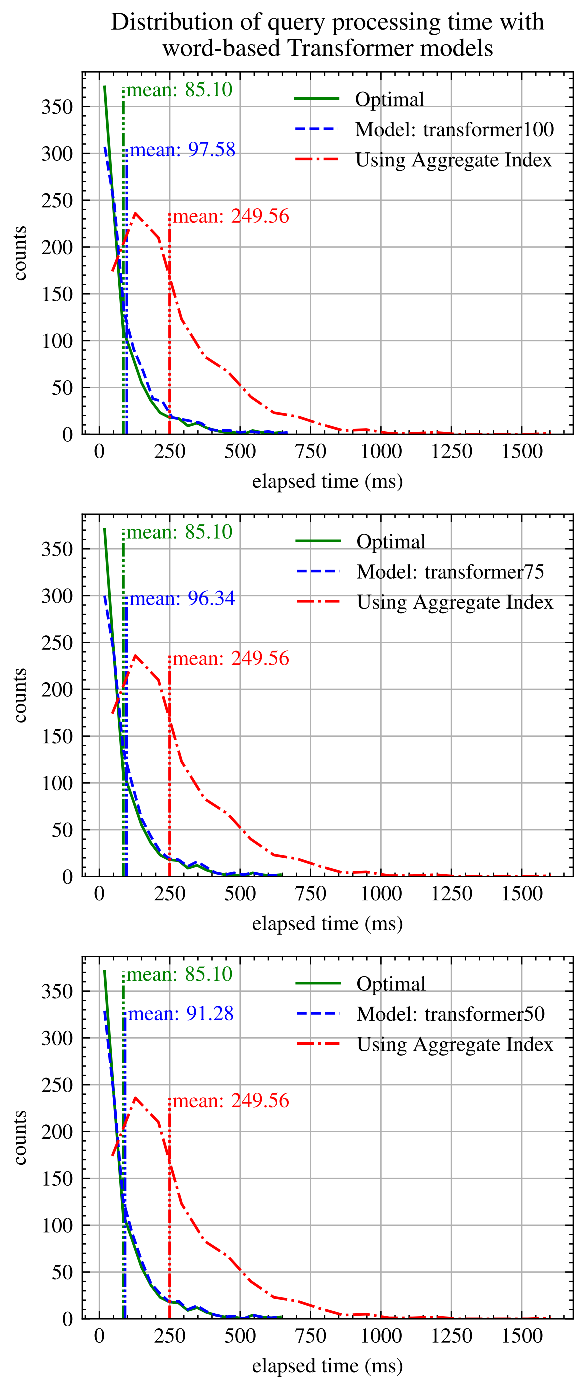
4.5.3.6 MLP-Mixer

*D*escription:

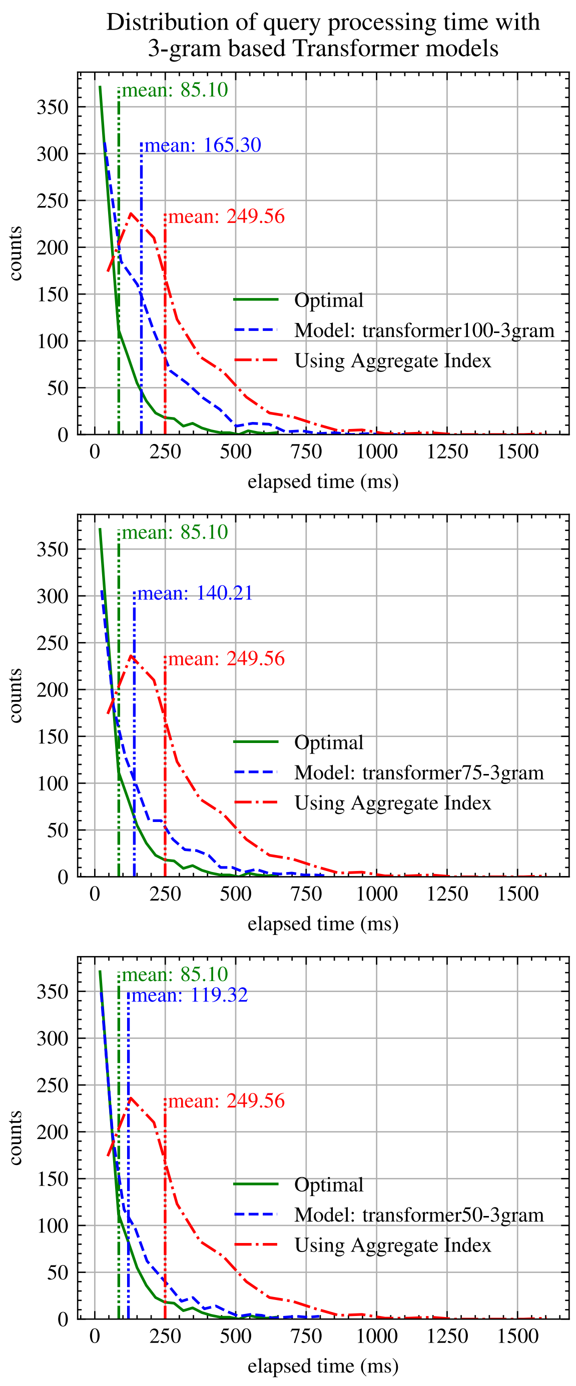
MLP-Mixer is an architecture based on MLPs only, which is proposed by Tolstikhin et al. [**DBLP:journals/corr/abs-2105-01601**]. It is intended for computer vision. However, we want to see whether we could use it for our use case. In this experiment, we modify its architecture for text processing. The same minimalist approach and evaluation scenarios are used as in other experiments.

Model architecture:

- Each query is embedded into $\mathbb{R}^{L\times 64}$ where L is the token sequence length, which is used as the input to the Mixer Layer.

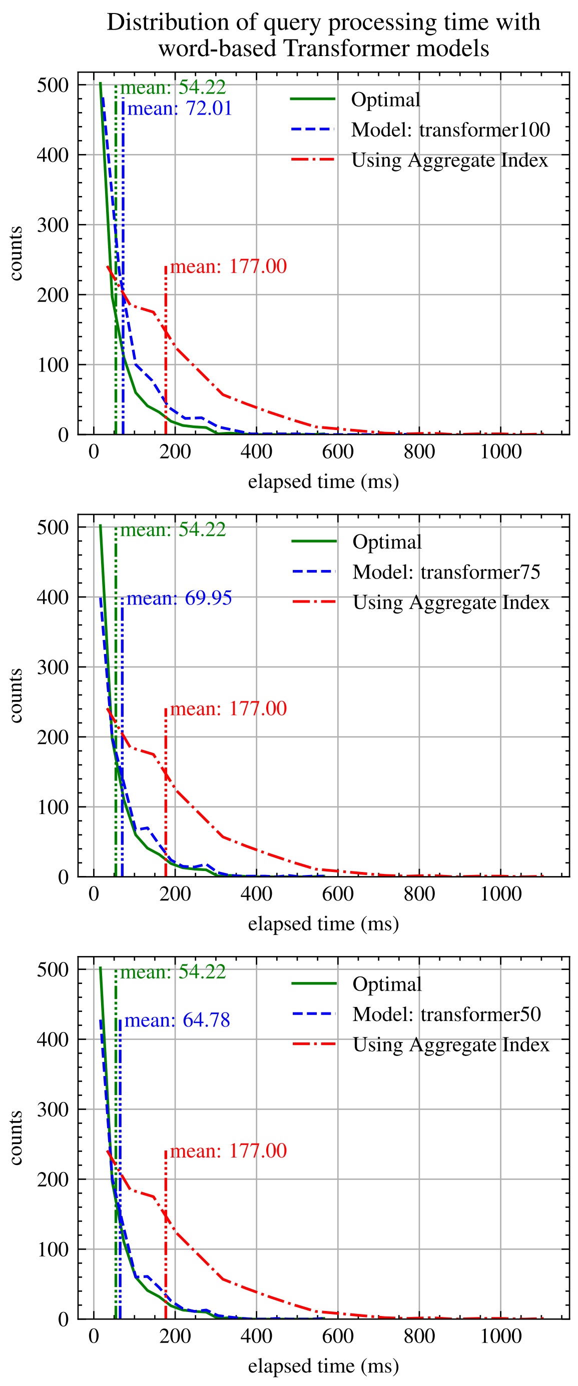


(a) Word-based Transformer models

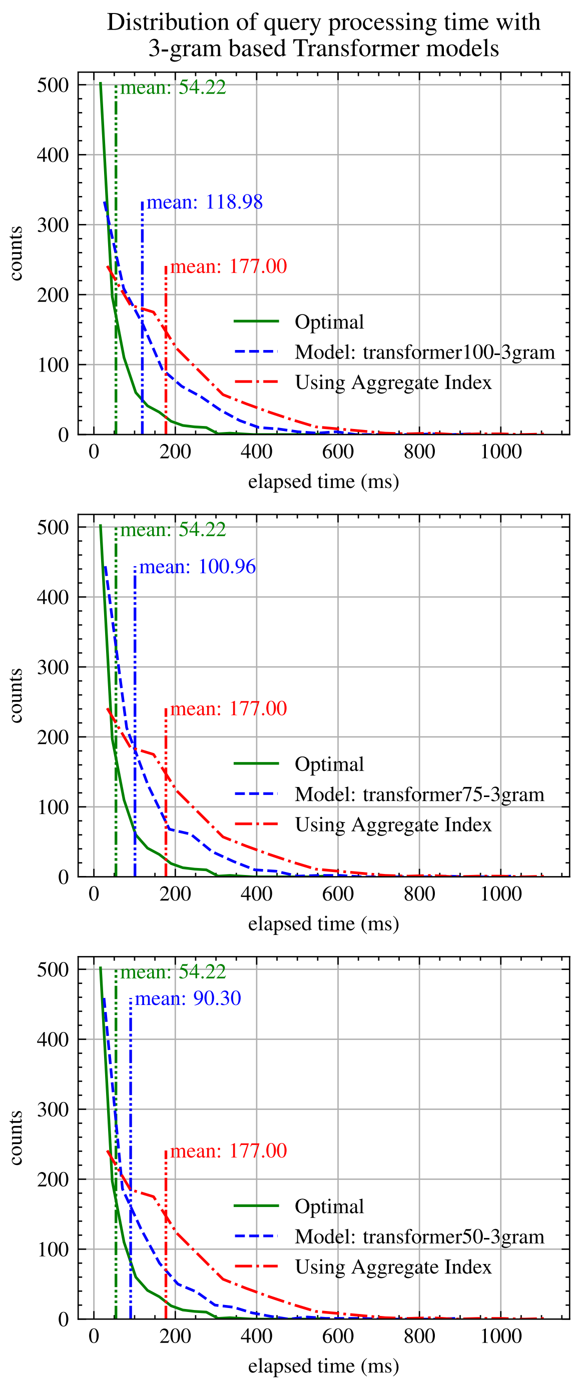


(b) 3-gram based Transformer models

Figure 4.20: Distribution of query processing time with Transformer models under the workload A.



(a) Word-based Transformer models



(b) 3-gram based Transformer models

Figure 4.21: Distribution of query processing time with Transformer models under the workload B.

- The Mixer Layer is implemented following the architecture presented in the paper [**DBLP:journals/corr/abs-2105-01601**].
- Layer normalization is applied to outputs from the Mixer Layer.
- We apply global max pooling to the outputs of layer normalization to generate a flat vector in $\mathbb{R}^{64}$, which is used as input to the output layer.

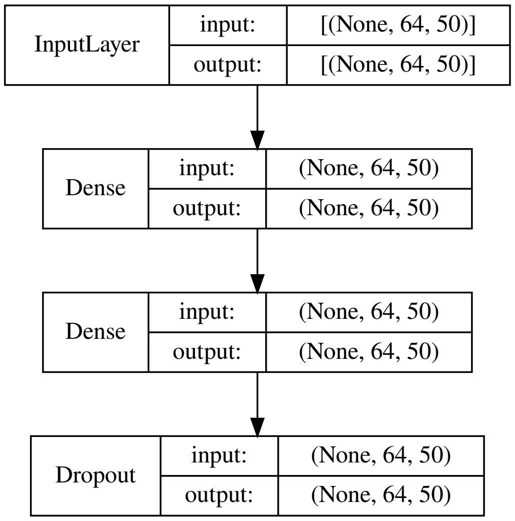
Figure **??** shows its architecture. The 6 trained MLP-Mixer models are listed in Table **??**.

Model name	**Training dataset**
mlpmixer100	100% attrs., word-based
mlpmixer100-3gram	100% attrs., 3-gram based
mlpmixer75	75% attrs., word-based
mlpmixer75-3gram	75% attrs., 3-gram based
mlpmixer50	50% attrs., word-based
mlpmixer50-3gram	50% attrs., 3-gram based

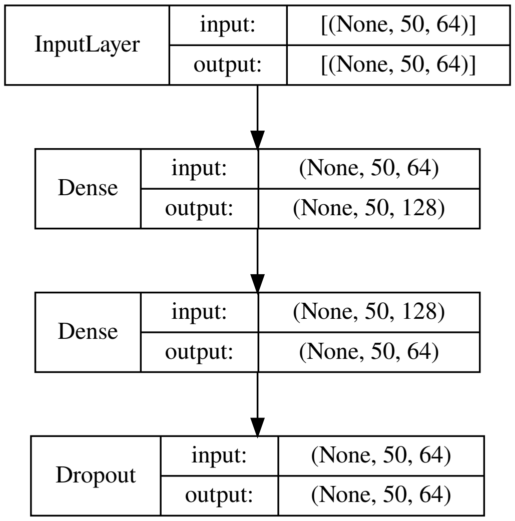
Table 4.13: MLP-Mixer model names and corresponding training datasets.

Observations:

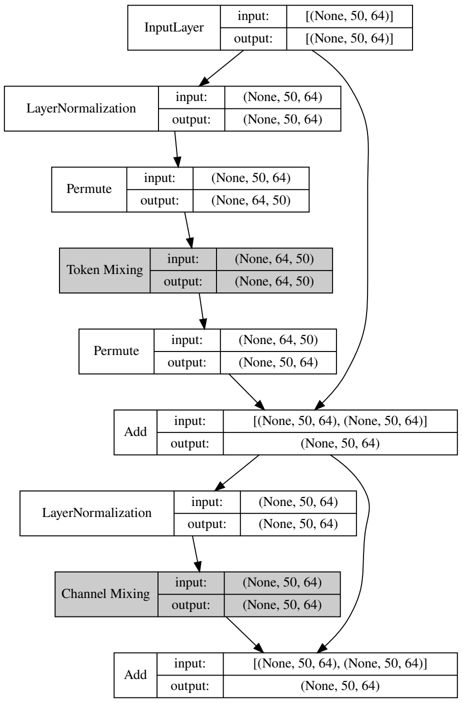
- The top-1 to top-5 accuracies for all variations of MLP-Mixer models under the workloads A and B are shown in Figure **??**.
- Figure **??** and Figure **??** show the distribution of query processing time under the workloads A and B, respectively. The word-based models perform slightly better than 3-gram based models, with the exception of two models $mlpmixer75$ and $mlpmixer75\text{-}3gram$. In addition, the models trained using partial tuples with less attributes perform better than those trained using partial tuples with more attributes, with the exception of the model $mlpmixer75$ under the workload B.



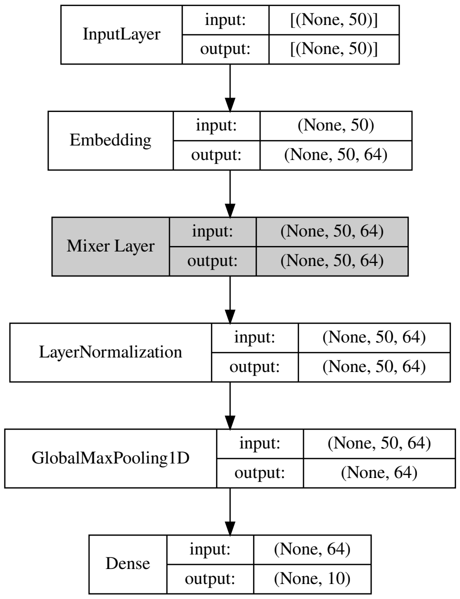
(a) Token mixing



(b) Channel mixing

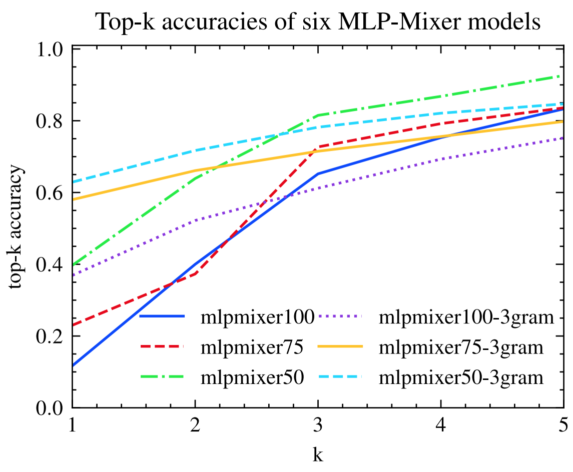


(c) Mixer Layer

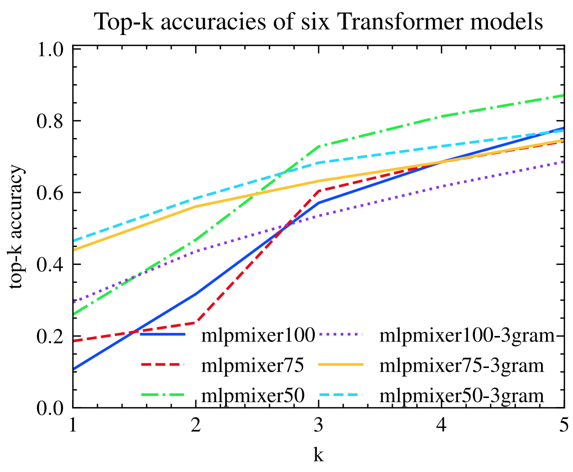


(d) Overall architecture

Figure 4.22: MLP-Mixer model



(a) Under the workload A.



(b) Under the workload B.

Figure 4.23: Top-k accuracies of six MLP-Mixer models under the workload A and B.

4.5.3.7 Comparison of different models

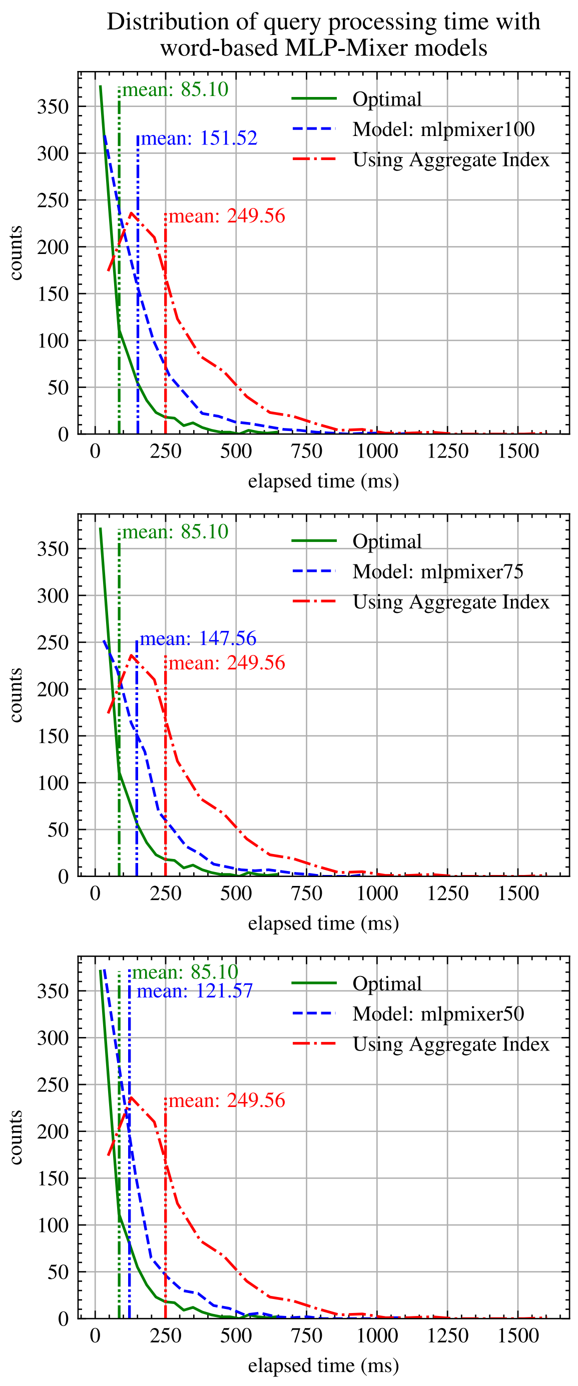
Based on the observations from Section **??** to Section **??**, we have compiled the following table to compare their relative performances with respect to the optimal and the aggregate index lookup under the workload A.

	Word tokens			3-gram tokens		
Model	parameters	$\frac{\text{model}}{\text{optimal}}$	$\frac{\text{model}}{\text{aggr}}$	parameters	$\frac{\text{model}}{\text{optimal}}$	$\frac{\text{model}}{\text{aggr}}$
MLP	3.02M	**1.10**	0.37	272K	**1.49**	0.51
LSTM	3.05M	1.52	0.52	305K	1.78	0.61
Conv1D	3.03M	**1.12**	0.38	277K	1.68	0.57
Transformer	3.09M	**1.12**	0.38	340K	**1.66**	0.57
MLP Mixer	3.04M	1.65	0.56	287K	**1.65**	0.56

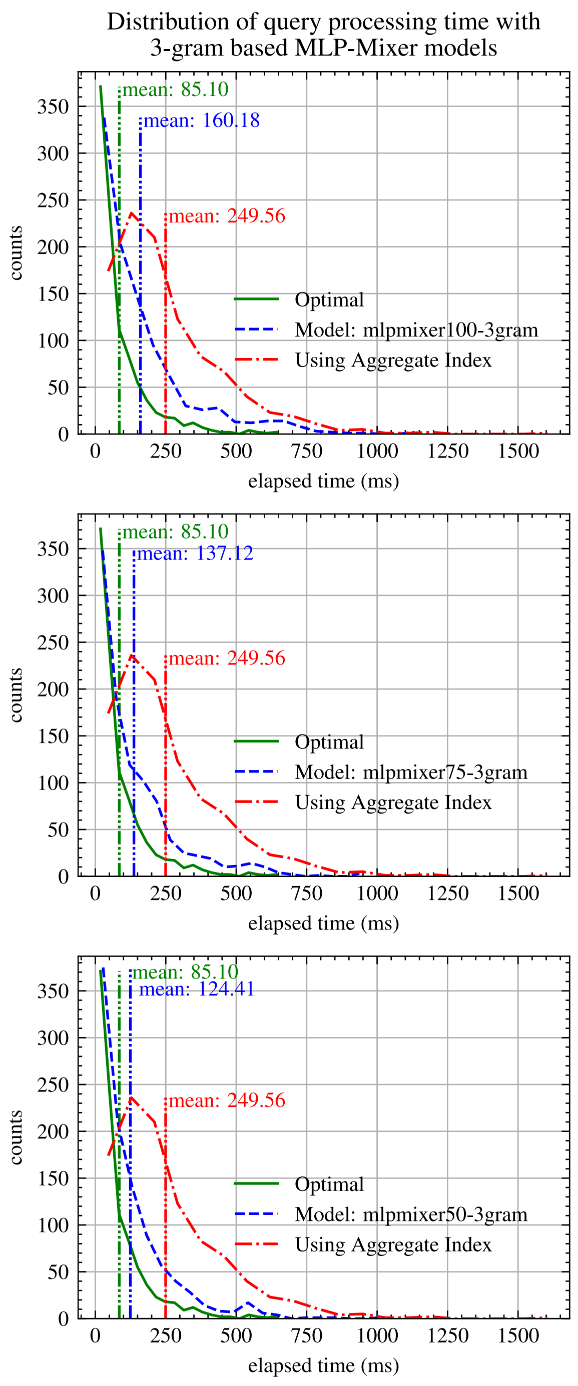
Table 4.14: Comparison of models under the workload A with the top-3 measurements highlighted.

The observation supports our proposal of utilizing neural networks to accelerate index lookup. As shown in Table **??**, many of the models perform well compared to the optimal index lookup, and significantly outperform the aggregate index lookup.

For word based tokens, MLP is only 10% slower than the optimal index lookup,

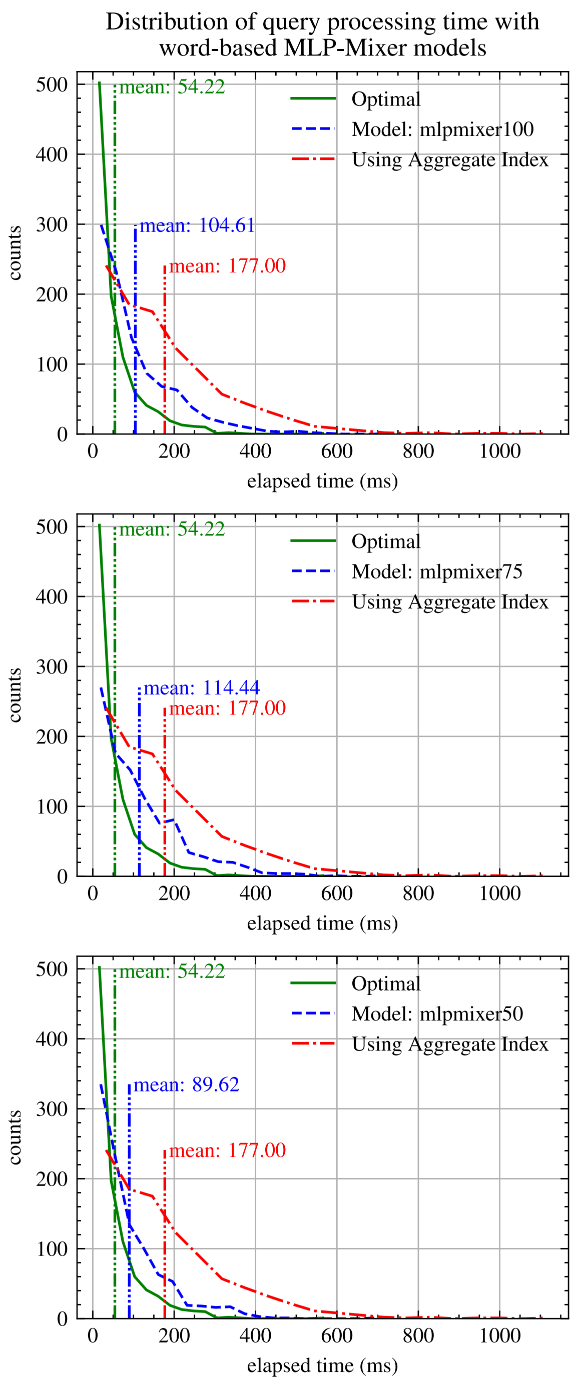


(a) Word-based MLP-Mixer models

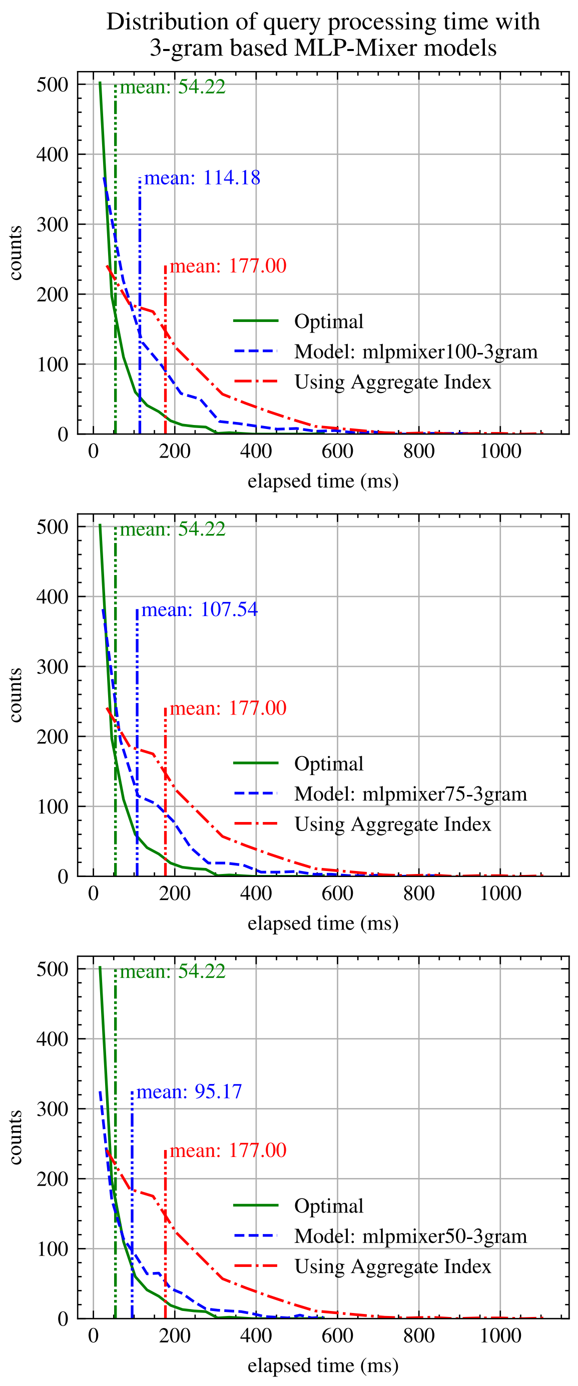


(b) 3-gram based MLP-Mixer models

Figure 4.24: Distribution of query processing time with MLP-Mixer models under the workload A.



(a) Word-based MLP-Mixer models



(b) 3-gram based MLP-Mixer models

Figure 4.25: Distribution of query processing time with MLP-Mixer models under the workload B.

and outperforms the aggregate index by almost 3 times. The Conv1D and Transformer are only slightly worse than MLP. But the transformer models have larger model sizes. Both LSTM and MLP Mixer do not perform that well when compared to the other three networks.

We realize that we only use one transformer block and one MLP Mixer Layer, respectively. In our context, we are interested in embedded networks as part of the query processor. Therefore, our focus is limited to small network architectures.

Regarding the model sizes, the main source of parameters is the embedding layer. Word based tokens produce far more bigger vocabulary, which then requires many more embedding vectors as model parameters. The vocabulary of 3-grams is much smaller, and thus produces much more compact models.

Since 3-gram tokens individually capture less information than word-based tokens, we expect the observed performance degradation when using the 3-gram tokens. With that being said, MLP has shown to outperform the aggregate index with twice the performance even for 3-grams.

The value of 3-gram vocabularies becomes more apparent in scenarios with noisy queries. When query strings contain spelling and other noises at a sub-word level, the two methods of tokenization, i.e., word-based and 3-gram based, behave quite differently. For word-based tokenization, noisy words will generate out-of-vocabulary (OOV) tokens which do not contribute to the classification of the network. However, the 3-gram tokenization can still produce *some* 3-gram tokens even for misspelled and unknown words in a query string. The next section is dedicated to evaluate how well word-based and 3-gram based networks behave in the presence of noisy queries.

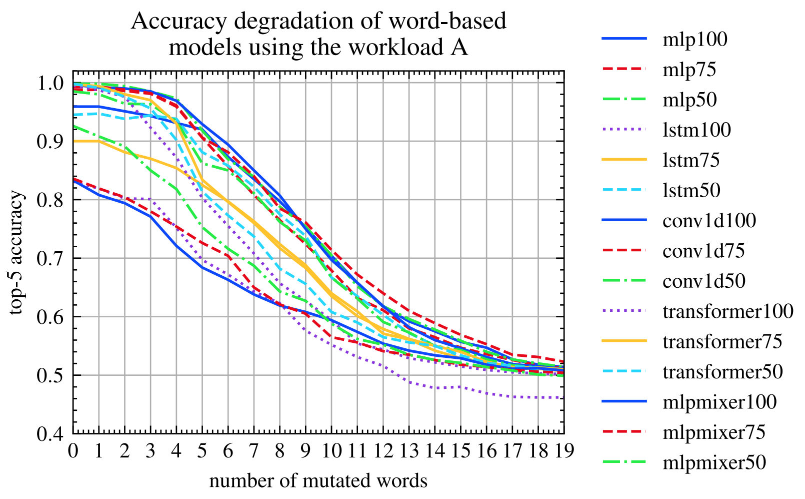
4.5.4 Impact of noisy queries on models' performance

*D*escriptions:

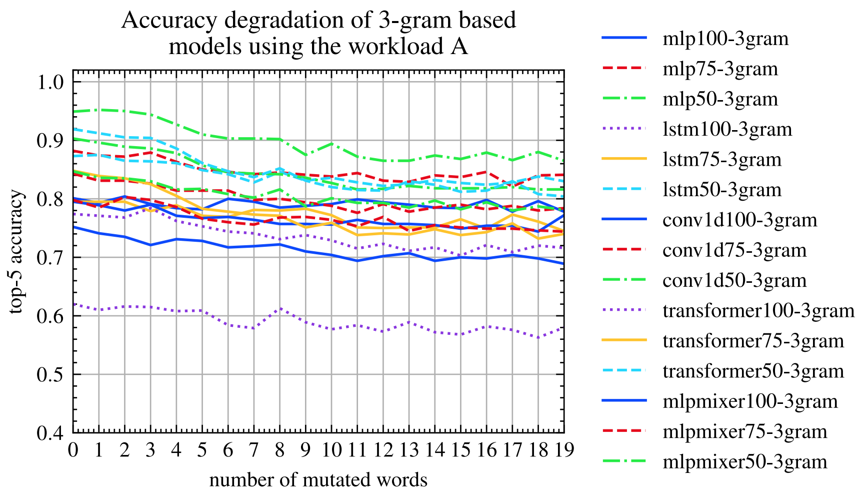
In this experiment, we investigate the impact of misspelled words in queries on the models' performance of top-5 accuracy. We simulate the scenario by replacing a randomly selected character in a word with the special character "_". For example, the city name `toronto` becomes `to_onto` after mutation. Its 3-gram tokens will be `[__t, _to, to_, o_o, _on, ont, nto, to_, o__]`.

Observations:

The impact of noisy queries on models' performance of top-5 accuracy is shown in Figure **??** and **??** under the workload A and B, respectively. The performance degradation of word-based models is much faster than that of 3-gram based models. This clearly shows that 3-gram based models are more resilient to query noises.

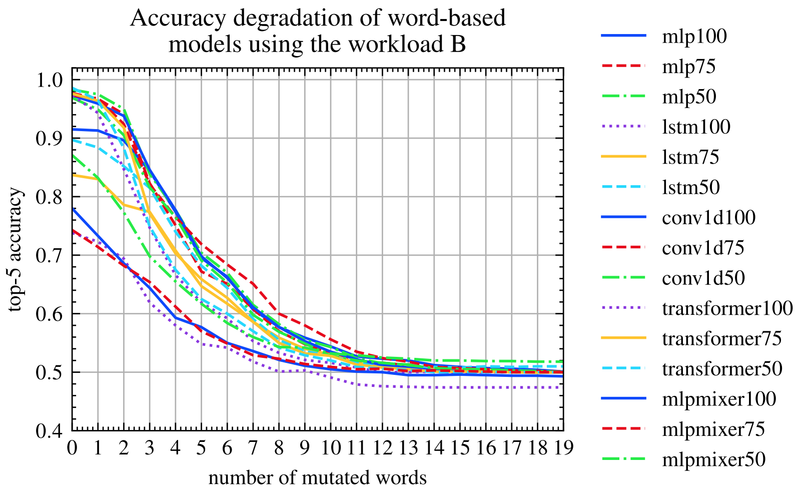


(a) Word-based models

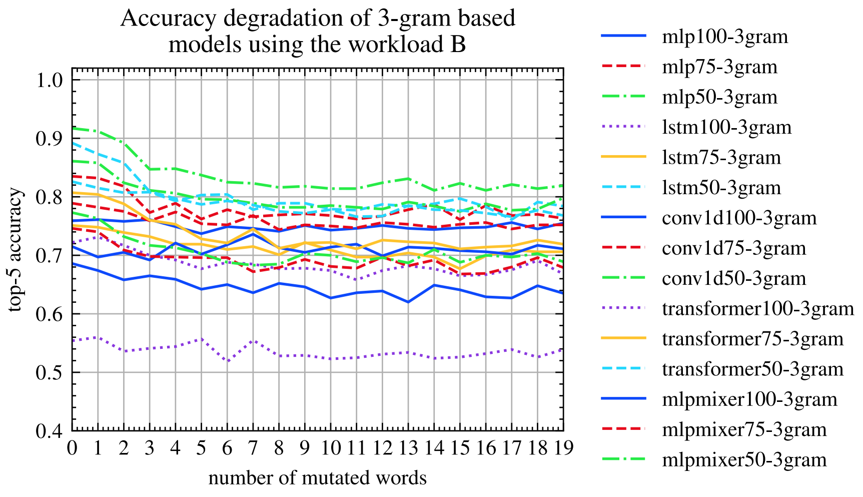


(b) 3-gram based models

Figure 4.26: Top-5 accuracy degradation of all models under the workload A.



(a) Word-based models



(b) 3-gram based models

Figure 4.27: Top-5 accuracy degradation of all models under the workload B3.

Chapter 5

Related Work

5.1 Relational keyword search

A lot of work has been done for relational keyword search. In this section, we review some of the previous works.

Early papers: Hristidis and Papakonstantinou [**hristidis2002discover**] presented DISCOVER, a system that allowed users to submit keyword queries to relational databases without the knowledge of the underlying database schema. DISCOVER processes keyword queries to generate candidate networks of relations and create execution plans to be submitted to RDBMS, which will return search results. Liu et al. [**liu2006effective**] proposed an information retrieval (IR) ranking strategy for effective keyword search related to relational databases. The ranking strategy used four normalization factors for computing ranking scores. All answers of a query were ranked based on computed ranking scores, and the top-k answers were returned as results.

Extension to include frequent co-occurring term (FCT): Tao and Yu [**tao2009finding**] proposed an operator called frequent co-occurring term (FCT) search, and an algorithm that could solve FCT search effectively without using the conventional keyword search methods. The purpose of FCT search is to extract the terms that most accurately represent a set of keywords, i.e., to discover the concepts closely related to the keywords set.

Survey of keyword search: A survey about research on keyword search in relational databases was done by Park and Lee [**park2011keyword**]. First they listed fundamental characteristics of keyword search in relational databases: an indexing structure, being able to formalize internal queries based on query keywords, being able to correctly constructing candidate answers, and an answer ranking strategy. Then they investigated five research dimensions, including data representation, ranking, efficient processing, query representation, and result presentation. At the end, they pointed out some promising research directions. One of them is efficient top-k query processing. The authors believed that keyword search in relational databases would benefit from advance in top-k query processing techniques.

Interpretation of keywords in query: Zeng et al. [**zeng2012isearch**] presented a framework based on keyword query interpretations. It incorporated human feedback to remove keyword vaguenesses and use a ranking model for query interpretation evaluation afterwards.

Top-k recommendation: Meng et al. [**meng2017top**] presented an approach to solve typical and semantically related queries to a given query. This can help users to explore their query intentions and improve their query formulation.

5.2 Machine learning based database optimization

Index optimization: Ding et al. [**ding2020alex**] presented an updatable learned index called ALEX, an in-memory index structure, for index optimization. ALEX addressed practical issues related to various types of workloads with dynamic updates. RadixSpline [**kipf2020radixspline**], another learned index, tackled the issue of index implementation difficulty. RadixSpline offered quick build using a single pass over data while achieving competitive performance.

Query optimization: Bao [**marcus2022bao**] is a learned query optimization system using reinforcement learning. It can learn from mistakes and adapt to dynamic workloads, data, and schema, thus is capable of applying per-query optimization hints.

Cost models for query processing: Siddiqui1 et al. [**siddiqui2020cost**] investigated how to learn cost models from cloud workloads for big data systems. The learned cost models could be integrated with existing query optimizers. Such a query optimizer could make accurate cost predictions, which can improve resource efficiency in big data systems.

Chapter 6

Conclusions and Future Work

In this chapter, we summarize our work and describe possible continuing work that could be done in future.

6.1 Summary

Contributions from our work can be summarized as:

- We propose partial tuple search as an extension of keyword search over relational data. It is a generalization of keyword search by allowing users to submit partial tuple queries, which can have both value-based keywords and schema-based structure information. Partial tuple search can be used by users with limited, but nonzero, knowledge over the schema of the underlying relational database.

- We demonstrate a query processing pipeline that can evaluate partial tuple search queries efficiently. It consists of four main steps: convert a partial tuple to a keyword query, use an embedded neural network classifier to predict a dynamic access pattern of partitioned full-text indexes based on the keyword query, scan indexes to find top-k candidates, and finally complete the partial tuple by finding an optimal match.

The pipeline requires indexing each relation to a separate full-text index. It also needs a trained neural network classifier using sampled tuples from each relation.

- We identify bottleneck related to performing fuzzy string matching when using a monolithic full-text index. The bottleneck is related to the inverted index data structure used in a full-text index. When using 3-gram tokenization to support fuzzy string matching, severe hash collision will happen because the number of documents is a lot bigger than that of 3-gram search terms. The performance will degrade from log-time $\mathcal{O}(\log n)$ to sequential scan $\mathcal{O}(n)$.

- We design an index partition scheme to speed up index lookup. We partition tuples by their corresponding relations, i.e., each relation is indexed into a separate full-text index. The partitioned indexes give us an opportunity to optimize query evaluation by using a neural network. This approach does not incur the additional costs of parallel CPU loads.

- We design self-supervised neural networks to optimize partitioned index access, which is incorporated in the query processing pipeline. We use relation names as labels to avoid manual labelling of training data, which are generated using sampled tuples from each relation.

- Our experimental evaluation shows that small neural networks work well for our use case. Our MLP models perform particularly well, while Conv1D models and MLP based transformer models are pretty close. On the other hand, the 3-grams trained networks are highly robust w.r.t. spelling errors.

6.2 Discussion of limitations and Future work

As described in Section **??**, we assume that the counts of relations' tuples are not skewed, and that the vocabulary of the database is not affected by any operation applied to the database.

If the first assumption is violated, for example, one relation has an extremely large number of tuples, our approach of partitioning index based on relations can not effectively tackle the bottleneck related to the inverted index any more. The partitioned indexes corresponding to large relations will have the same bottleneck caused by hashing collision in the inverted index data structure. Therefore, we will have to partition large relations based on some criteria. The key is to have the resultant partitions having different vocabularies, which could help training a more accurate neural network. We could partition a large relation by attributes or attribute values.

- Partition a large relation by dividing its attributes into subsets. An intuition is to group attributes with similar vocabulary into the same partition. Thus, different partitions are likely to have quite different vocabularies.

- Partition a large relation based on certain attribute values. For example, if a relation has an attribute about "city", we can divide the relation by city names. Each partition holds the data for a continuous range of the first letter of the city name, e.g., A-I, J-R and S-Z. The key of this approach is to pick an appropriate partition key for the relation.

- To the end of having partitions with vocabularies as different as possible, the first partitioning scheme could be a better option. This is because different attributes in a relation usually have different sets of limited values. On the other hand, partitions resulting from grouping by certain attribute values will have the same schema as the original relation, which means they are more likely to have similar vocabulary.

This is a possible future work direction that can improve the solutions proposed in the thesis.

Regarding the second assumption, if the vocabulary of the database changes, we can apply fine-tuning to the neural network classifier.

- We freeze the network and apply incremental fine-tuning to embeddings only. We could freeze existing embeddings and only train new embeddings, or fine-tune all embeddings.
- We don't freeze the network. We simply apply fine-tuning to both embeddings and the network. This approach will take longer training time than the first approach. But since our network is relatively small, the extra training time is likely not significant.

This can be another direction of future work.

The current sizes of our neural networks are small enough to be embedded in a mobile application. For deployment scenarios involving a backend server, we can relax its size limit. This means that we can design deeper neural network architectures that are still embeddable in a system running on a server. In order to do that, we will need to resort to automatic tuning of hyperparameters to find optimal network designs. This can be an interesting future work, too.

Our work uses full-text index, Apache Lucene in particular, to index relational data and evaluate partial tuple queries. A possible future work is to integrate partial tuple search into existing RDBMS. This would give users a more flexible and powerful way to query relational databases.