



# Ingegneria dei dati

# Homework 1

A.A. 2024/2025

TOPIC: Speech Recognition

TEAM: **Data Hunters**

Members:

- **Luca Borrelli**
- **Rainer Cabral Ilao**



# Homework Objectives

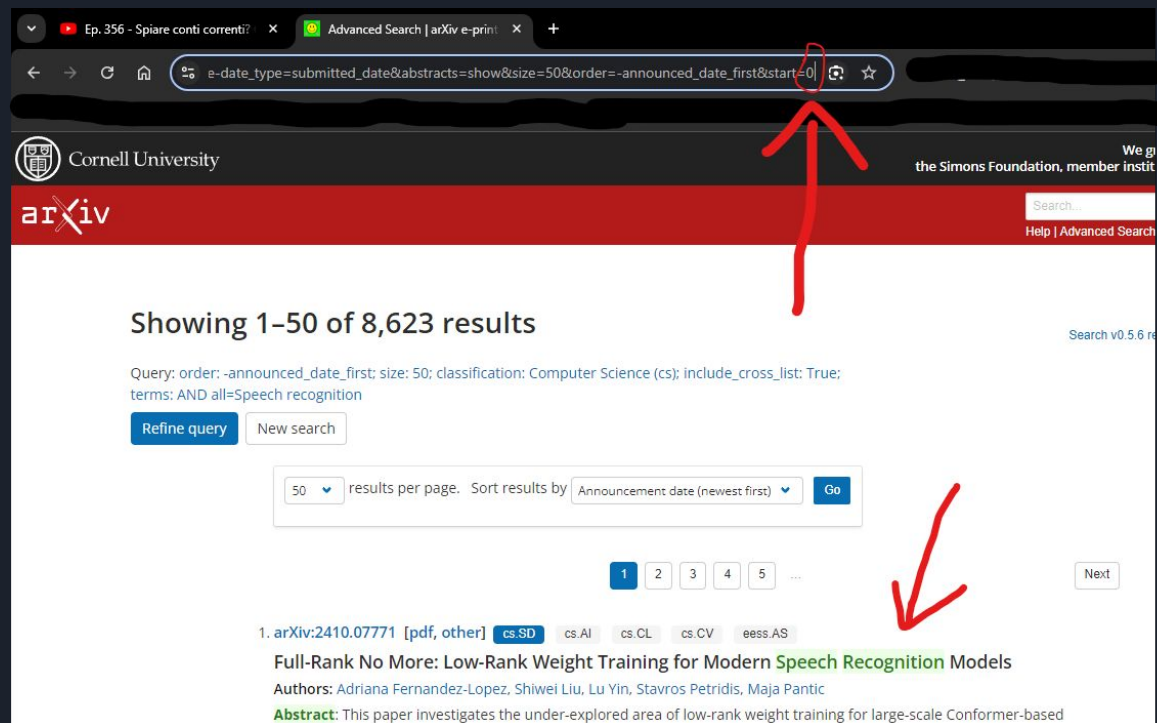
Learn to extract relevant data from scientific sources in Computer Science, focusing on data organization and cleanliness for effective use.

Consolidate techniques for data extraction from HTML using XPath.

## Phases

1. **Download and Clean Papers:** Acquire 498 HTML articles for data extraction.
2. **Extract and Organize Data:** Extract key information and format it into structured JSON for analysis.
3. **Analysis:** quality of phase 2

# Phase 1.1: Download of Search Pages



The screenshot shows the arXiv Advanced Search interface. A red arrow points to the address bar, which contains the URL: `e-date_type=submitted_date&abstracts=show&size=50&order=-announced_date_first&start=0`. Another red arrow points to the search results list. The first result is titled "Full-Rank No More: Low-Rank Weight Training for Modern Speech Recognition Models" by Adriana Fernandez-Lopez, Shiwei Liu, Lu Yin, Stavros Petridis, and Maja Pantic. The abstract states: "This paper investigates the under-explored area of low-rank weight training for large-scale Conformer-based".

Ep. 356 - Spiare conti correnti? x Advanced Search | arXiv e-print x +

← → ↺ ↻ e-date\_type=submitted\_date&abstracts=show&size=50&order=-announced\_date\_first&start=0 ↺ ☆

Cornell University the Simons Foundation, member instit We g

arXiv Search... Help | Advanced Search

Showing 1-50 of 8,623 results

Query: order: -announced\_date\_first; size: 50; classification: Computer Science (cs); include\_cross\_list: True; terms: AND all=Speech recognition

Refine query New search

50 results per page. Sort results by Announcement date (newest first) Go

1 2 3 4 5 ... Next

1. arXiv:2410.07771 [pdf, other] cs.SD cs.AI cs.CL cs.CV eess.AS

**Full-Rank No More: Low-Rank Weight Training for Modern Speech Recognition Models**

Authors: Adriana Fernandez-Lopez, Shiwei Liu, Lu Yin, Stavros Petridis, Maja Pantic

**Abstract:** This paper investigates the under-explored area of low-rank weight training for large-scale Conformer-based

We utilized the internal search engine of arXiv for targeted research on the topic.

This allowed us to obtain search pages containing links to relevant papers.




## Phase 1.1: How to download a html page from Url?

```
# Funzione per il donwload di una pagina mhtml nella cartella searchPages
def download_html(url):
    try:
        risposta = requests.get(url)
        risposta.raise_for_status() # Gestisce errori di rete
        return risposta.text # Restituisce il contenuto HTML come stringa
    except requests.exceptions.RequestException as e:
        print(f"Errore durante il download della pagina: {e}")
        return None # Restituisce None se la richiesta fallisce
```

To automatically download the search pages from the links, we simply used the [requests](#) library, one of the most well-known for this task.

We saved the HTML pages of the search results in the designated folder 'searchPages'.



## Phase 1.2: How to extract right links of papers from Search Pages?

The next step involved the initial phase of data extraction from the 21 pages.

Using Python code, we retrieved the paper links from each search page with the following XPath query:

```
//ol[@class='breathe-horizontal']//li//div//p//a[contains(@href, 'abs')].
```

This extracted a set of URLs in the format:

```
https://arxiv.org/abs/2409.12156.
```

The Python code then modified each link by replacing the 'x' with a '5' and saved the modified link to a text file, along with the corresponding code from the last portion of the link.



The library used for the XPath expression was BeautifulSoup.

# Phase 1.3: Download of Papers

From the text file, we downloaded all the papers for each URL into HTML files within the sources folder.

We simply reused the same code used for the SearchPages.

## EfficientASR: Speech Recognition Network Compression via Attention Redundancy and Chunk-Level FFN Optimization

Jianzong Wang<sup>1,2</sup>, Ziqi Liang<sup>1,2</sup>, Xulong Zhang<sup>1</sup>, Ning Cheng<sup>1</sup>, Jing Xiao<sup>1</sup>  Equal Contributions  Corresponding author: Xulong Zhang (zhangxulong@ieee.org). <sup>1</sup>Ping An Technology (Shenzhen) Co., Ltd. <sup>2</sup>University of Science and Technology of China

### Abstract

In recent years, Transformer networks have shown remarkable performance in speech recognition tasks. However, their deployment poses challenges due to high computational and storage resource consumption. This paper, aiming to enhance the versatility of Transformer models. EfficientASR employs two primary modules: Shared Residual Multi-Head Attention (SRMHA) and Chunk-Level Feedforward Network (CLFFN). The CLFFN module captures spatial knowledge and reduces the number of parameters. The effectiveness of the EfficientASR model is validated on two public datasets, namely Aishell-1 and HKUST Transformer network, along with improvements of 0.3% and 0.2% in Character Error Rate (CER) on the Aishell-1 and HKUST datasets, respectively.

### Index Terms:

speech recognition, attention redundancy, feedforward network, lightweight

## I Introduction

In recent years, Transformers [1] have shown better performance than traditional sequence models [2, 3] in the ASR domain, capturing long-range dependencies through attention mechanisms. Attention mechanisms map different positions through identity mapping. However, attention computation in Transformers is computationally expensive and contains a significant amount of redundancy. On the other hand, feedforward networks (FFNs) capture local dependencies, but this also leads to an increase in network parameters. These issues result in high-performing Transformer models requiring substantial storage and computational resources, making it difficult to deploy on edge devices.

The importance of attention mechanisms in Transformer networks has been extensively studied. For instance, He et al. [4] introduced the residual attention mechanism to improve model performance. They revealed that as attention propagates from lower to higher layers, the attention distribution becomes more diagonalized, with higher-layer attention contributing less to model performance. Additionally, Shim et al. [7] found that lower-layer attention focuses more on semantic features of speech, while higher-layer attention focuses more on phonetic features. They discovered that attention distributions between adjacent layers tend to be more similar, reducing network redundancy by sharing certain attention heads. HybridFormer [9] proposed HyperMixer to reduce redundancy and improve information respectively. Benefit from HyperMixer's linear time and memory complexity, significantly reducing computational and memory costs.

*Example of html page*



## Phase 1.4: **Problems** of Phase 1.3

During the download, we faced three main issues:

1. The server at <https://arxiv.org/> sometimes rejected our requests, leading to only 595 papers downloaded instead of 1,000.
2. Not all HTML pages were actual papers; some were previews instead.
3. Some pages were corrupted or empty, causing script execution problems.



## Phase 1.4: How to **resolve** Problem 2?

```
html_pages = os.listdir("sources")

for page in html_pages:
    with open("sources/" + page, "r", encoding="utf-8") as file:
        html_content = file.read()

        soup = BeautifulSoup(html_content, 'html.parser')

        if soup.find("a", class_="is-sr-only") != None:
            os.remove(f"sources/{page}")
```

To remove HTML files that were previews of the papers, we checked each file for a specific tag thanks to xPath expression.

Using a Python script, we deleted those files, leaving only the actual papers.

After this process, the number of valid papers decreased from 595 to 498 papers.



## Phase 2: How to extract right data from sources?

```
# query xpath che serviranno per estrarre le informazioni
queries = {
    "figures": "//figure[contains(@class, 'ltx_table')]",
    "caption": "../figcaption//text()",
    "html_table": "./div | ./table | ./p",
    "table_id": "./@id",
    "footnotes": "../figcaption[contains(text(), 'Note')]/text()",
    "footnotes_bli": "../cite//a/text() | ../cite//span/text()",
    "paragraphs": "//div[contains(@class, 'ltx_para')]/p | //div[contains(@class, 'ltx_para ltx_noindent')]/p"
}
```

To extract the required data from each paper, we utilized specific XPath queries with the **lxml** library.

The selection of these queries was based on analyzing the HTML structure of the papers, which were generally similar.

We also used the **json** library to manage and generate the JSON file for each paper.



## Phase 2: How to extract right data from sources?

The function `extract_info_from_html` processes an HTML file of a paper to extract relevant information for each table. It does so by:

1. Table ID: Extracted using an XPath query to locate the identifier (e.g., "S4.T3") of the table within the HTML structure.
2. table\_html: the html tag is extracted using figures present in the paper that has "ltx\_table" class
3. Caption: Retrieved by parsing the text associated with each table's caption, also using an XPath query.
4. Footnotes:
  - a. Note into tables or figure-caption.

There was a second version:

- b. Old Second option: Citation numbers within each table are identified through `<cite>` tags, and corresponding footnotes are extracted from other sections of the document by linking the citation number to its detailed text.

Duplicate footnotes are removed for clarity.

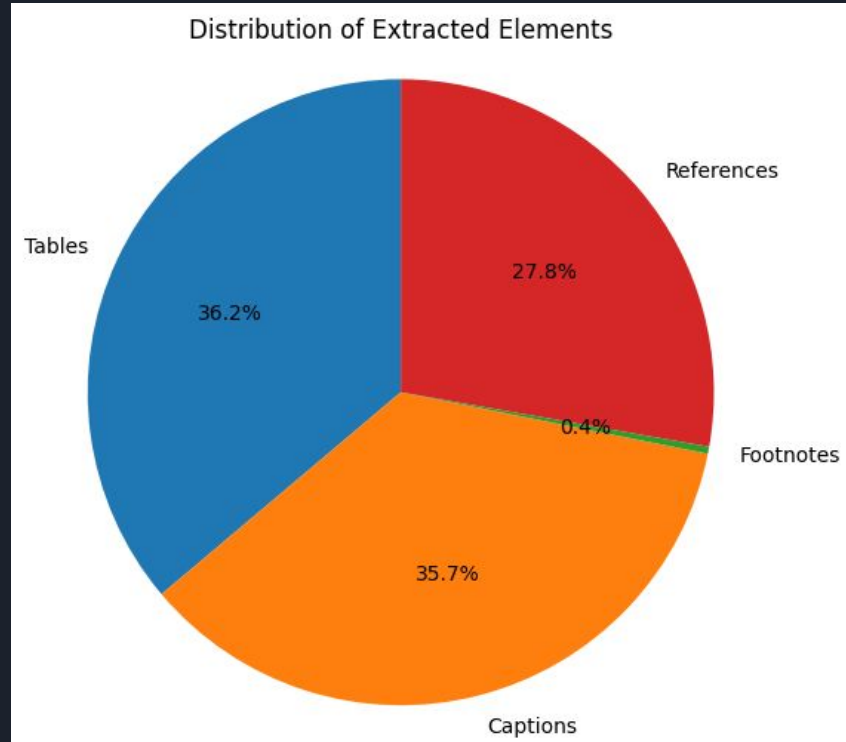
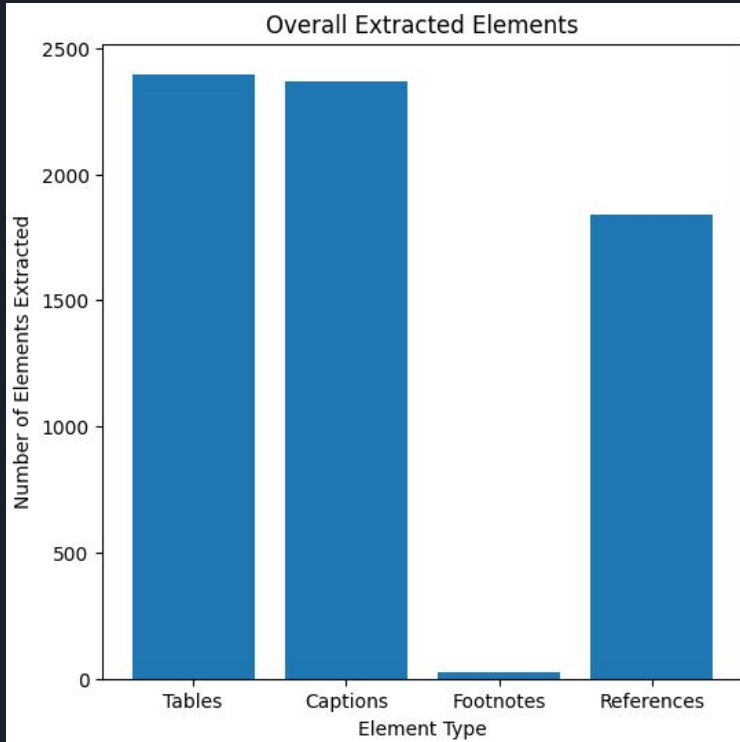
5. References: The function dynamically builds an XPath query to find paragraphs referencing the table, using the caption text to locate links pointing to the table. These references are cleaned to remove HTML tags, leaving only the textual content.

# Phase 2: Result

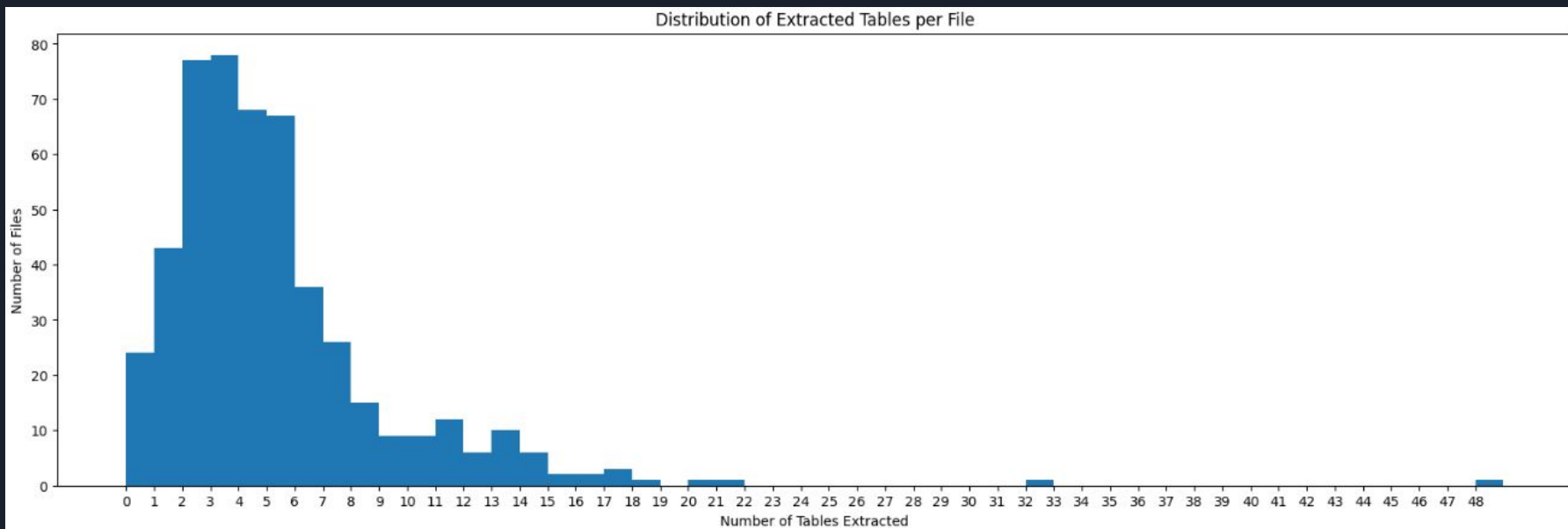
Example of  
JSON file

```
{
  "S4.T1": {
    "caption": "Table 1: Summary of Word Error Rate (WER) of the two models with/without GPT in Fleurs and KSC test sets.",
    "table": "<figure id=\"S4.T1\" class=\"ltx_table\">\n<figcaption class=\"ltx_caption\"><span class=\"ltx_tag ltx_tag_table\">Table 1: </span>\n",
    "footnotes": [],
    "references": [
      "After training the GPT model using text data, we conducted tests to measure its perplexity (ppl) on the Fleurs and KSC test sets. The per"
    ]
  },
  "S4.T2": {
    "caption": "Table 2: Results of models decoding with GPT, EOT Judgment Modification (EOT-JM), and Hallucination Penalty (HP) on Fleurs-test.",
    "table": "<figure id=\"S4.T2\" class=\"ltx_table\">\n<figcaption class=\"ltx_caption\"><span class=\"ltx_tag ltx_tag_table\">Table 2: </span>\n",
    "footnotes": [],
    "references": [
      "Table 2 presents the Word Error Rate (WER) of two models with each improvement step on Fleurs-test. For the EOT Judgment Modification (E"
    ]
  },
  "S4.T3": {
    "caption": "Table 3: Summary of WER for the Fleurs-test subset with a high average token log probability (ALP). The values highlighted in red",
    "table": "<figure id=\"S4.T3\" class=\"ltx_table\">\n<figcaption class=\"ltx_caption\"><span class=\"ltx_tag ltx_tag_table\">Table 3: </span>\n",
    "footnotes": [],
    "references": [
      "The system is able to calculate the average token log probability (ALP) for each sample during decoding, and ALP values are usually stat"
    ]
  },
  "S4.T4": {
    "caption": "Table 4: Summary of the overall WER for systems leveraging unpaired speech and text data.",
    "table": "<figure id=\"S4.T4\" class=\"ltx_table\">\n<figcaption class=\"ltx_caption\"><span class=\"ltx_tag ltx_tag_table\">Table 4: </span>\n",
    "footnotes": [],
    "references": [
      "Table 4 summarizes the WER of systems leveraging unpaired speech and text data. The selection of system (3) corresponds to the best resu"
    ]
  }
}
```

## Phase 3: Analysis of Distribution of objects



## Phase 3: Distribution of number of tables



*Avg of #table for each file: 4.87*

## Phase 3: Analysis of Distribution of References

Total number of tables: 2397

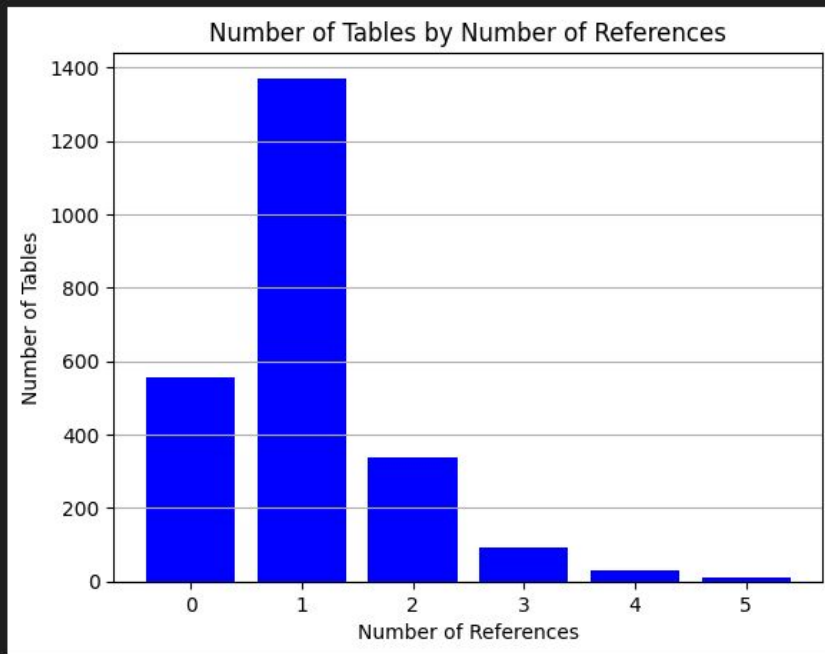
Table with the maximum number of references: 58.T4 with 5 references

Table with the minimum number of references: 55.T1 with 1 references

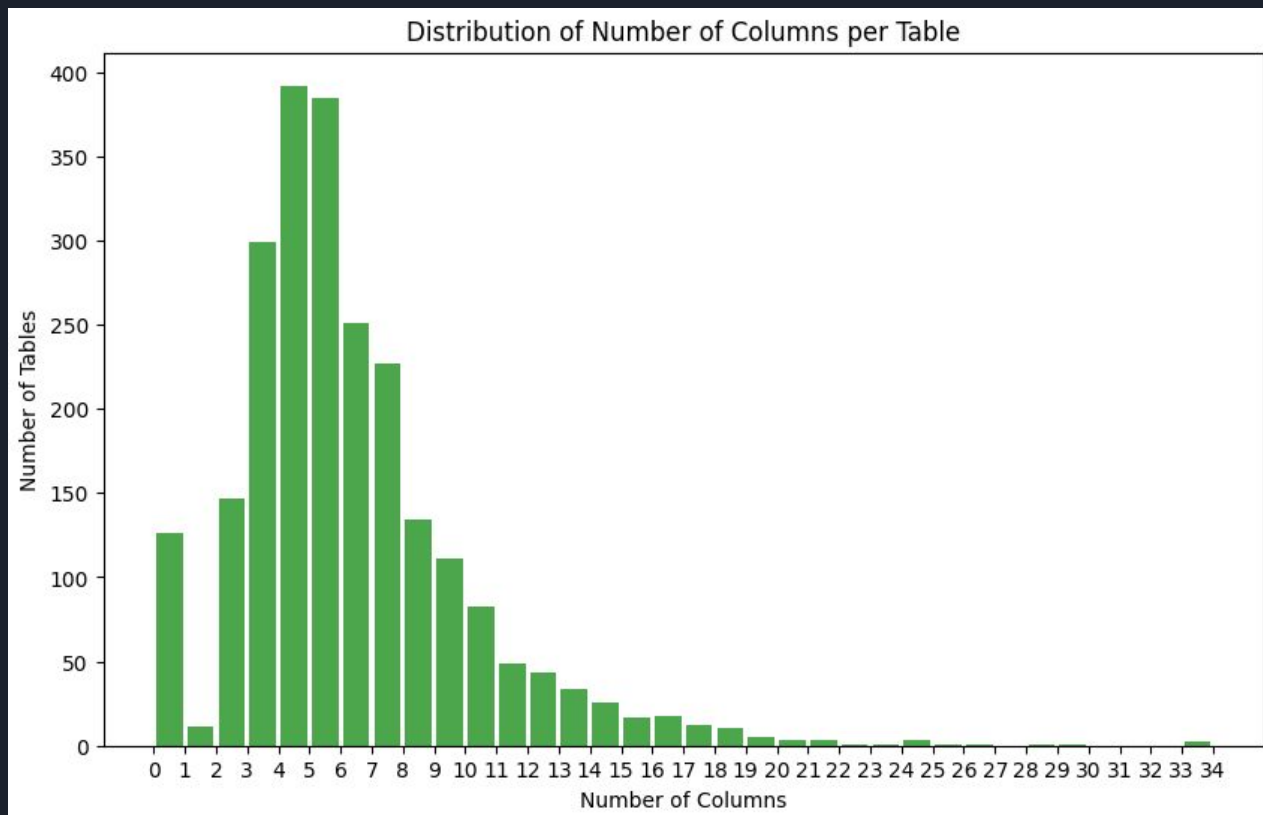
Count of tables without references: 555

Mean number of references: 1.04

Standard deviation of references: 0.84



## Phase 3: Analysis of distribution of Number of Columns per Table





# Challenges

- Table recognition
- Search of footnotes
- Heterogeneous document structure
- Presence of images or graphics





# What we have learned

- Learn how to use XPath extensively as a tool for extracting data with precise patterns within HTML code.
- Cleaning data for easy visualization



# Thank you for your Attention

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