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Using machine learning models for processing the data presented to the user by mobile devices.

**Bachelor's thesis
in COMPUTER SCIENCE**

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Abstract

In the era of rapidly evolving digital applications, traditional scraping techniques face increasing challenges in maintaining reliable data collection pipelines. Commissioned by Murmuras, a company specializing in commercial and scientific data analysis, in this project we present a novel approach to processing phone screen content, such as displayed social media posts and website advertisements. Our solution leverages Large Language Models (LLMs) running locally on the user's device to handle diverse data formats while ensuring that sensitive information remains protected. The primary application explored in this study is the extraction of discount coupons, demonstrating the feasibility of our method in identifying and structuring valuable content from varying digital sources. Furthermore, the system is designed to be easily adaptable to other use cases, such as analyzing users' political views. Additionally we explore usage of non-LLM models for the defined task. The results highlight the potential of LLM-driven content analysis as an alternative to conventional scraping techniques.

Keywords

LLM, NLP, BERT, Android, Edge-device, Fine-Tuning

Thesis domain (Socrates-Erasmus subject area codes)

11.4 Artificial Intelligence

Subject classification

I.2.7: Natural Language Processing
H.3.3: Information Search and Retrieval

Tytuł pracy w języku polskim

Wykorzystanie modeli uczenia maszynowego do przetwarzania danych zaprezentowanych użytkownikowi przez urządzenie mobilne.

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Chapter 1

Introduction

1.1. Project background and motivation

With the rapid advancement of information technology, the Internet has become one of the most crucial facets for many businesses to perform marketing activities [7]. One of the key marketing tools in business-to-consumer (B2C) e-commerce is the digital coupon [10]. Compared to paper coupons, digital coupons are characterized by their wide reach, rapid distribution, and low spread costs. Furthermore, a key advantage of digital coupons is their ability to facilitate targeted marketing by offering personalized discounts to different customers, thereby increasing sales [7].

Recent statistics underscore the significance of mobile devices in the domain of coupon distribution. For example, studies have shown that over 90% of digital coupon users access their vouchers via smartphones [13], and similar figures are reported by other industry sources [14]. This high rate of mobile usage creates a pressing need for coupon analysis tools that are optimized for mobile platforms, ensuring that consumers receive timely and personalized offers regardless of their location or device.

Large Language Models (LLMs) have become a fundamental technique in contemporary machine learning, replacing previously utilized recurrent neural network (RNN) architectures in the field of natural language processing (NLP) [8]. Subsequent research has demonstrated their applicability to structured input data [9], such as screen views and coupons. Additionally, there have been efforts to integrate these models into web scraping pipelines [18].

In light of these trends, the company Murmuras has tasked us with developing a solution based on a machine learning model that can be deployed as a mobile application. This model will process input representing the user's onscreen view and extract digital coupons along with their relevant data. This solution must be capable of running locally on the device, ensuring efficient processing without relying on external servers. By leveraging advanced machine learning techniques, the app will handle the diverse formats and layouts of digital coupons, thus facilitating the collection of data regarding coupons.

1.2. The definition of a coupon

A coupon is a physical piece of paper or digital voucher that can be redeemed for a financial discount when purchasing a product [3]. A coupon is characterized by a name, expiration date, and a discount type, e.g. '20% off', 'buy 1 get 1 free', etc., however, not every coupon contains each of these features. Furthermore, coupons may contain numerous other features such as images and eligibility requirements. Henceforth, the term 'coupon' will refer exclusively to a

digital coupon. The term 'conventional coupon' will refer to the traditional physical coupon. Examples of digital coupons encountered in mobile applications are presented in 1.3

Figure 1.1: Example coupon from fast-food restaurants chain mobile application

Figure 1.2: Example coupon from grocery store mobile application

Figure 1.3: Example digital coupons

1.2.1. Our data model of digital coupon

In the following research we model a digital coupon as a collection of named fields:

1. *product_name*: the name of the product,

2. *valid_until*: the text representing the date of coupon expiration,

3. *discount_text*: the text representing the discount offered to the user,

4. *activated*: either true or false, indicates whether the coupon has been activated,

We allow for special *null* value in the above fields in case no data is available.

An example of a digital coupon represented in JSON format is shown in listing 1.1:

Listing 1.1: Example of a digital coupon in JSON format

```
{
    "product_name": "Shampoo X",
    "valid_unitl": "2025-06-30",
    "discount_text": "20% OFF",
    "activated": true
}
```

1.3. The Significance of the Digital Coupon

The digital coupon is one of the most important tool in contemporary marketing strategies [10], therefore analyzing their lifecycle is essential to maximize their benefits. To facilitate such analyses, researchers collect various statistical metrics, including the fraction of redeemed coupons among all distributed coupons referred henceforth as redemption rate [5] and customer engagement [6], while also assessing their impact on sales performance [6]. Additionally, studying competitors' digital coupon strategies enables businesses to identify market trends, adjust their promotional tactics, and maintain a competitive edge in the evolving digital marketplace.

Redemption Rate

The measurement of coupon redemption rates is primarily based on either survey data [4] or controlled experimental studies [5]. However, the company Murmuras [1] has introduced an alternative approach that enables the direct collection of coupon-related data from users' devices. This method utilizes a screen content scraping tool installed on the devices. Additionally, the tool has the ability to record user's actions. Having access to all the user's interactions and visual changes in the layout, it is possible to detect the coupon redemption. This allows for large-scale data acquisition while reducing the costs associated with traditional survey-based methods.

Customer Engagement and Impact on Sales

Customer engagement metrics, such as conversion rates and the effect of e-coupon issuance on sales, can potentially be measured using statistical analysis tools operating on the seller's website [2]. The conversion rate is typically derived by tracking visitor activity, while the impact on sales is estimated by correlating the updated conversion rate with the frequency of coupon issuance.

Although this approach provides valuable insights, it relies on direct collaboration with the coupon issuer and is constrained to a single webpage. Consequently, it is not applicable to our study, as we aim to analyze arbitrary mobile applications with diverse coupon designs.

1.4. Problem Statement

The objective of this work is to extract coupons visible to the user from the content displayed on a mobile device screen. The extracted coupons should be represented as a JSON list, with each entry conforming to the format specified in Section 1.2.1.

The screen content is provided in the form of a `.CSV` file, which encodes an XML tree structure representing the underlying screen layout. Each row in this file corresponds to a single view element within the screen hierarchy [15]. The dataset includes at least the following attributes:

1. **view_depth**: The depth of the view within the XML tree hierarchy.

2. **text**: The textual content displayed to the user within the view.

3. **id**: A unique identifier for a screen sample. Each sample consists of a set of views observed either simultaneously or in directly consecutive snapshots.

4. **time**: The timestamp indicating when the view was recorded.

5. **view_id**: The unique identifier assigned to the view by the Android API.

An example of the dataset to illustrate described format is provided in Table 1.1.

view_depth	text	id	time	view_id
2	"50% OFF"	101	12:30:15	`com.example.app:id/discount_label`
3	"Buy 1 Get 1 Free"	101	12:30:15	`com.example.app:id/promo_banner`
2	"Limited Offer"	102	12:31:05	`com.example.app:id/offer_text`

Table 1.1: Example of dataset format representing screen content.

Additional requirement is that the screen content processing will be performed exclusively on the end device to mitigate potential privacy concerns.

1.5. Project goals

1. A tool to process the data extracted from the device into a format suitable for use by the model.

2. A machine learning tool for extracting the data that is of interest to us, such as the coupon name, expiration dates, prices, etc. The model should be capable of handling various coupon formats and layouts with high accuracy.

3. An optional tool for post-processing the output data from the tool mentioned in the previous point into a common format.

4. An application that runs the above three tools on a mobile device. (Optional)

5. A key requirement is that the machine learning model must be deployable on the mobile device itself to guarantee data privacy.

1.6. Potential applications of the project

1.6.1. Assessing coupon effectiveness

The access to the content of mobile device screen allows us to list all the coupons seen by the user. Additionally, as we will retrieve information about coupon activation status, there will be possibility to track coupon redemptions by comparing the coupons models *active* field.

Given that, our solution will aid businesses in analyzing consumer behavior and optimizing their marketing strategies. By facilitating the collection of data on coupon characteristics and their redemption rates, businesses will be able to assess the effectiveness of their coupon campaigns—determining whether they achieve the desired results. Additionally, large-scale analysis of coupon data can reveal valuable insights into purchasing patterns, preferred discount types, and the most appealing products or services.

1.6.2. Market analysis and competitor monitoring

Machine learning is proven to be a useful tool in the field of market competitors analysis but it requires significant amounts of data[11]. The aforementioned gathering of data about displayed coupons can also be utilized in further monitoring of competitors' coupon strategies, their effectiveness, and whether they provide better discounts. Using machine learning to identify and analyze competitors' strategies is more cost-effective compared to exhaustive web scraping or mystery shopping [11]. This will enable businesses to make better informed decisions about their own marketing campaigns and provide a comprehensive understanding of the competitive landscape.

Chapter 2

Machine learning and the dangers associated with it

Over the past several years, artificial intelligence (AI) has been widely sensationalized in the media. Amid the promises of a utopian future, with self-driving cars and intelligent virtual assistants that dominate the headlines, concerns about AI are also growing. Many fear a future in which human labour has been made obsolete by automation and AI [29]. Privacy concerns are also mounting, as AI models are often trained on vast datasets that may include sensitive information such as healthcare records, biometric data for facial recognition, and financial details — sometimes collected without consent [31].

2.1. Understanding the difference artificial intelligence, machine learning and deep learning

Artificial intelligence (AI), machine learning (ML) and deep learning (DL) are terms often mistakenly used interchangeably to refer to the development of systems capable of performing tasks typically requiring human intelligence such as decision making and speech recognition [30]. AI is the umbrella term encompassing among others, machine learning and deep learning, as well as other approaches [29]. Machine learning is a subset of AI, in which systems are able to learn and adapt without explicit rules [30]. Deep learning is a type of machine learning utilizing neural networks. This hierarchy is depicted in the image below.
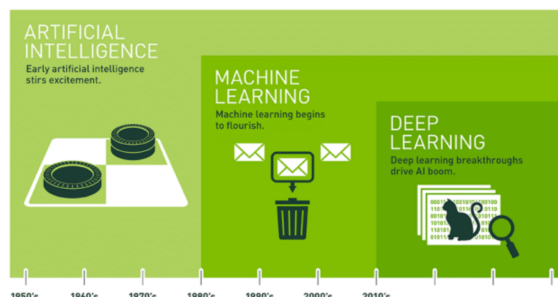

Figure 2.1: The hierarchy of artificial intelligence, machine learning and deep learning [29]

2.1.1. Artificial Intelligence

Artificial intelligence can be succinctly described as "the effort to automate intellectual tasks normally performed by humans." The field of AI encompasses various approaches, including machine learning and deep learning, which rely on data and statistical models to identify patterns and make decisions. However, the field also includes symbolic AI, which operates differently by relying solely on predefined rules rather than data-driven models [29]. An example of symbolic AI is expert systems like MYCIN, which used around 500 of IF-THEN rules to diagnose bacterial infections and recommend treatments with accuracy on par with human specialists and better than general practitioners [32].

2.1.2. Machine Learning

On the other hand, machine learning is a branch of artificial intelligence in which the machine is trained rather than explicitly programmed, by making inferences from the input data it is presented with [29]. Two major types of machine learning are supervised and unsupervised learning.

Supervised learning refers to an approach that relies on labeled datasets to train or "supervise" the model. The model is provided with input data along with the correct output, allowing it to learn by example. The model analyzes the relationship between the input features and the corresponding labels, gradually improving its ability to make accurate predictions. Supervised learning is commonly used for tasks such as classification, where data is sorted into categories, and regression, where numerical values are predicted based on patterns in the data. This method is widely applied in real-world scenarios like email spam detection, image recognition, and sales forecasting.

In contrast, unsupervised learning involves the model analyzing, clustering unlabeled data and identifying patterns without guidance from the programmer or datasets, hence it is called unsupervised learning. Unsupervised learning can be used to identify groups of products often purchased together [33].

In this project, we primarily employ supervised learning to develop our solution. This choice is driven by the nature of the problem, which involves identifying coupons from a screen view presented as an XML tree and extracting relevant data from them. Since this task is essentially a classification problem — where the goal is to categorize elements rather than uncover hidden patterns or group data points — supervised learning is the most suitable approach. By leveraging labeled data, the model can effectively learn to recognize and extract the desired information with accuracy and efficiency.

2.1.3. Deep Learning

Deep learning is a subset of machine learning wherein multilayered neural networks, called deep neural networks, are utilized to learn increasingly meaningful representations with each successive layer as seen in 2.2; each representation is increasingly different from the original and more useful to determining the result. Traditionally, machine learning models focus on learning one or two layers of representations of the data [29], deep learning employs at least three layers, and typically hundreds or thousands of layers to train the models [48].

The transformation implemented by a layer is defined (parametrized) by its *weights*, which are numerical parameters. Learning involves adjusting these weights to ensure the network accurately maps inputs to their corresponding targets. A deep neural network can have millions of parameters, making it challenging to find the right values since changing one parameter affects the others. To guide this process, a *loss function* measures how far the
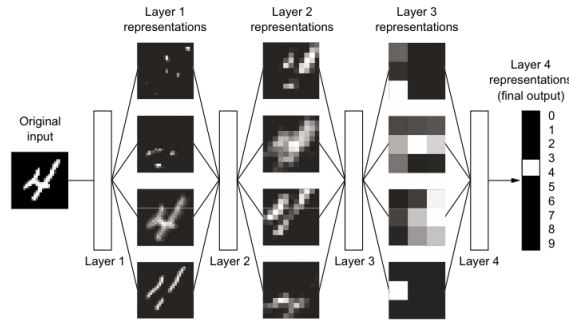
Figure 2.2: Data representations learned by a digit-classification model [29]
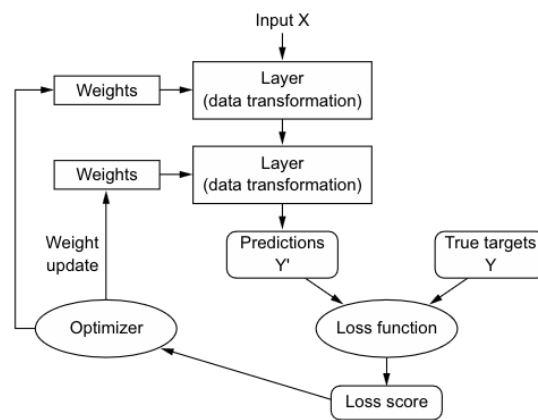

Figure 2.3: A visualization of how a Deep Learning model works [29]

network's predictions deviate from the expected results, providing a score that reflects its performance. Deep learning relies on using the loss score as feedback to adjust the network's weights, guided by the optimizer using the backpropagation algorithm. Initially, the weights are random, resulting in poor predictions and a high loss score. With each example, the optimizer tweaks the weights to reduce the loss. Repeating this process across many examples gradually minimizes the loss, producing a trained network that closely matches its target outputs. This process is exemplified in 2.3 [29].

The advancement of deep learning contributed to the development of generative AI such as ChatGPT as well as Natural Language Processing (NLP) which enables machines understand and generate text and speech. This is useful for translations and extracting meaning from large quantities of data [48].

2.2. Should We Be Afraid of AI? - Assessing the Risks and Ethical Implications of Artificial Intelligence

As artificial intelligence becomes increasingly complex and integrated into our daily lives, the voices raising concerns about its dangers grow louder. Some express concern about the risks of excessive surveillance and privacy erosion, envisioning a future where AI systems are deeply

intertwined with our surroundings, essentially hearing what we hear and seeing what we see [35]. Others highlight the environmental challenges tied to large-scale AI deployment, such as rising energy and water consumption, along with the need for rare materials in microchip production [36]. This section will focus on assessing the risks of artificial intelligence and how our solution will take them into account.

2.2.1. Privacy Erosion

AI systems heavily rely on vast amounts of user data to deploy machine learning techniques that identify subtle patterns and behaviors that may not be immediately evident, thus enabling personalized recommendations [39]. Social media platforms like TikTok exemplify this, as their algorithms suggest content based on users' previous interactions [37] [38]. While this personalization enhances user engagement, it also risks influencing people's opinions and shaping their worldview by trapping them in ideological echo chambers.

Consequently, 'information privacy' is one of the primary concerns surrounding the use of AI. 'Information privacy' refers to the protection of personal data that is being collected, processed and stored by AI systems [40]. Training machine learning models typically requires immense datasets, involving terabytes or even petabytes of information. Therefore, these training sets likely include sensitive user information such as healthcare records and biometric data [41]. Beyond explicit data collection, AI systems can also infer highly personal attributes, such as political beliefs, sexual orientation, or health conditions, from seemingly unrelated data — a phenomenon known as 'predictive harm' [40]. This information can be utilized to subject individuals to targeted advertising, unwanted profiling, and even identity theft, often without the user's consent or awareness [39], thus posing a serious privacy risk.

Moreover, AI systems can pose 'autonomy harms', wherein the insights derived from data are used to influence individuals' decisions or behavior without their knowledge or proper consent. The common mindset of having "nothing to hide" overlooks the broader implications of these practices, which can undermine personal freedom and informed decision-making. A significant example of this problem is the Facebook-Cambridge Analytica scandal, in which a seemingly benign personality quiz was utilized to harvest over 87 million Facebook users' data. Based on this data, detailed psychological profiles were constructed and leveraged to target individuals with personalized political ads during the 2016 US Presidential Election. This case underscores how AI can extract deeply personal insights from mundane user interactions, demonstrating the potential for misuse when data privacy protections are inadequate [40].

To address privacy concerns associated with AI systems, we are implementing locally-deployable models that process data directly on users' devices. This ensures that raw, un-processed information never leaves the device or gets transmitted to external servers. By keeping data local, we significantly reduce the risk of unauthorized access, data breaches, or misuse. This approach empowers users with greater control over their information while still benefiting from the capabilities of AI in a secure and privacy-conscious manner.

2.2.2. Environmental Concerns

AI has a notable carbon footprint due to its increasing energy consumption, particularly during model training and usage [42]. One study predicts that by 2027, AI-related energy consumption could reach 85–134 TWh, representing nearly 0.5% of today's global electricity usage. This estimate is based on the energy consumption of the Nvidia A100 servers - the hardware estimated to be used by 95 percent of the A.I. market, and their projected sales in the upcoming years [43]. Training LLMs typically requires significantly more energy in comparison

to making a single prediction on the trained model [44], for instance BERT required "the energy of a round-trip transcontinental flight" to train, while GPT-3 emitted 552 metric tons of carbon dioxide which is "the equivalent of 123 gasoline-powered passenger vehicles driven for one year" [45].

Furthermore, while a quarter of the world lacks access to clean water and sanitation, data centers consume significant quantities of water during their construction and during operation to cool electrical components [47]. AI server cooling requires up to 9 liters of water per kWh of energy used. Given the amount of energy required to train and operate a model, this will exacerbate the lack of water, with UN estimates stating that by 2030 half of the world's population will be facing severe water stress [46]. It is estimated that globally, infrastructure related to AI will soon require six times more water than Denmark [47].

Chapter 3

Overview of Existing Solutions

To the best of our knowledge, at the time of this project's commissioning, no publicly available solutions directly addressed this problem. The most comparable approaches involve existing multimodal models. While widely used models such as ChatGPT and Gemini provide general data extraction capabilities [16], they are unsuitable for our task due to their substantial computational requirements. A key limitation of these models is their large size—for example, GPT-3 consists of 175 billion parameters[17]—rendering them impractical for deployment on mobile devices [27].

Alternatively, computer vision models can be used to extract text and bounding boxes from screen images. Microsoft's OmniParser [24], for instance, has demonstrated strong performance on the ScreenSpot dataset [24, 25]. However, the challenge of organizing extracted text into structured coupon data renders this approach unsuitable for our study. Furthermore, our experiments with running OmniParser locally on example images indicate that it relies on CUDA technology, making it impractical for deployment on mobile devices.

3.1. Murmuras' existing solution

Murmuras' current approach relies on a set of fixed scrapping programms tailored to specific layouts from limited set of applications, making it inflexible and expansive to generalize across diverse coupon formats. This lack of adaptability limits its usefulness in real-world scenarios where coupon structures vary widely. Since our goal is to develop a solution that is easily adaptable for processing diverse mobile content, this method is not well-suited for our needs.

In contrast, Murmuras' most-recent proof of concept involves wrapping the `CSV` data with a prompt that instructs the model and sending it to GPT-4o-mini. This approach leverages an LLM to interpret the data to extract relevant coupon details. However, the reliance on an external server means the solution does not run locally on the mobile device, leading to potential privacy concerns, latency issues, and a dependence on internet connectivity.

3.2. Scapegraph AI

ScrapeGraphAI is an open-source library that streamlines data extraction from websites and local documents by utilizing LLMs and graph logic to construct scraping pipelines [18]. The library supports integration with various LLMs, including local models through the use of Ollama [19] [20].

However, Scrapepraph AI provides only Python and Node.js SDKs [21], which could prove to be an issue with regard to mobile deployment, because neither Python nor Node.js is

natively supported on iOS or Android [22] [23].

Moreover, due to mobile devices typically having limited processing power and memory compared to desktop computers or servers [26], we cannot solely rely on the size of the model in order to improve performance. We believe that through fine-tuning LLMs, we are able to develop tools that are far more viable for edge device usage.

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