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競爭動態：剖析企業競爭行動與預測未來行動組合

Competitive dynamics: Profiling firms’ competitive actions and predicting future repertoire

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還記得剛進到 BI Lab 時，聽學長姐報告論文時毫無頭緒，老師曾說：「之後慢慢的聽多了就會了」；碩士生涯轉瞬即逝，好像纔剛剛開始學會讀論文，就要自己寫一篇了。寫一篇論文要克服的坎一道一道，從發想題目到建立模型，從想一個適合解決的問題到說出一引人入勝的故事，每一件事都很難。

很難，但我很幸運。很幸運成為魏老師的學生，老師總是能夠在我亂無章法的的想法當中找到收斂的線索，即便我沒有想法，也能硬是闢開一條新的路徑。每每跟老師對談，都覺得又有好多問題獲得解答，即便和學術研究毫無關係，老師的關心和提點對一個年輕的靈魂而言就像是恰到好處的澆灌，高度尊重我們卻又很有影響力。

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研究路途上遇到許多及時的幫助，希望有一天我也可以成為這樣幫助別人的人，把過去這段時日獲得的支持與幫助持續傳遞。

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摘要

在變動迅速的商業世界中，企業之間的互動與關聯顯得益發複雜，以至於確實了解競爭對手並精準地預判其可能之競爭行爲即顯得至關緊要。這些競爭行爲相當常見，舉凡價格戰、行銷企劃、訴訟等皆屬之；而當一家企業發起這樣的行爲時，其競爭對手也會因此迅捷地反應，調整自己的策略，以求不再競爭行列中脫隊。是故，若企業能夠有效地分析當下的競爭態勢，乃至於精確地預測出其競爭對手的潛在行爲，將大大地有助益。然因搜集競爭資料並進行全面分析會引發之成本甚鉅，要做到有效分析、精確預測並不容易。

本研究從「競爭動態」的角度出發，試分析企業所面臨之競爭態勢。競爭動態是一個以競爭行爲爲主體、描繪在策略層面上，競業之間如何反覆利用不同行爲進行競爭的框架。我們看到過去的文獻已針對競爭動態進行一定的研究，包含進行個案探討、提出解釋性模型等，然而我們亦發現，預測競爭行爲本身之相關文獻甚少，實爲該領域有待深掘之處。我們因此在本研究中提出一個涵蓋競爭行爲之分類、分群與預測的端到端的分析流程。我們搜羅了大量新聞文件，建構了一自動分類器來將文件依所提及之競爭行爲分類、整合，藉此爲每家標的企業梳理出其過往的歷史競爭行爲。接著，我們分別利用二種不同的方法——依文件共同提及或是共同歷史行爲——爲標的企業識別出其最主要的競爭企業以便爲標的企業建構其競爭態勢。根據標的企業的競爭態勢，我們提出了一個以閘門循環單元（GRU）和注意力機制（Attention）爲基底的時間序列預測模型，該模型被用來預測標的企業在下一個時間點所會進行之不同競爭行爲之次數。

此研究主要集中在航空業，其不但以高度競爭聞名，資料也相對容易取得，過去研究和其使用的公開新聞資料的量體就證明了這一點。我們使用與航空公司相關的新聞文件資料進行實驗，並證明建構以深度學習爲基底的時間序列預測模型會表現得比傳統統計模型更佳；我們也探討了用不同方法識別競爭對手如何影

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響預測結果。這項研究不僅能協助產業內的企業進行決策，我們的預測結果亦對投資者、第三方諮詢行業提供資訊，成爲其決策過程的一部分。

關鍵字：競爭動態、競爭行爲、競爭者識別、文件分類、漸增式分群、時間序列預測

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Abstract

In a fast-paced business world, interactions between firms are increasingly complex, making the understanding and prediction of competitors' actions critical for strategic decision-making. Competitive actions often include price wars, marketing campaigns, litigations, and more. When such actions are initiated, it is crucial for rival firms to react swiftly and update their strategies to maintain their market positions. Therefore, firms benefit significantly from effectively analyzing the current competitive landscape and predicting future actions to gain an advantage over their competitors. However, performing such predictions is challenging due to the difficulty in data collection and efficient comprehension.

In this study, we analyze the competitive landscape through the lens of competitive dynamics, an action-based perspective that investigates how rival firms compete through specific actions within their strategic contexts. Although previous studies in this field have proposed case studies and explanatory models to estimate the volume and complexity of competitive actions, directly predicting the occurrences of specific competitive actions has not been extensively explored. Our study presents an end-to-end pipeline to profile and forecast firms' competitive actions using advanced machine learning techniques. By leveraging a large dataset of news articles, we built an auto-profiler that annotates articles and consolidates them to form competitive events for each firm. We then identify the main competitors for a firm based on criteria such as co-mentioning in articles and the frequency of performing matching actions. Finally, we constructed a time series prediction model incorporating Gated Recurrent Unit (GRU) and Attention mechanisms capable of predicting the frequency of certain competitive actions in the future.

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Our study focuses mainly on the airline industry, which is known for its high competitiveness and the relative ease of obtaining data, as evidenced by previous research and the frequency of public news data. Using a dataset of airline-related news articles, our experiments demonstrate that deep learning-based time series prediction models outperform traditional statistical models. We also examine how different mechanisms for competitor identification affect the prediction outcomes. This study is beneficial not only to industry players but also to investors and third-party advisors, as they can incorporate the prediction results into their decision-making processes.

Keywords: competitive dynamics, competitive actions, competitor identification, text classification, incremental clustering, time series prediction

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1. Introduction

1.1. Background

Under the impact of globalization, firms are now drawn closer to each other, leading to stronger ties between different entities in the business world. Said firms are currently faced with business interactions that are getting increasingly complex, hence the need for advanced inter-firm competitive action analysis methods. Normally, the competitive actions we witness in the real commerce world include litigations, introducing promotion campaigns, price wars, fighting over resources, or any other move that challenges the status quo of the market process (Ferrier et al., 1999). Such competitive firm behavior can be attributed to the relational context of a firm, which aims for outperforming other firms lying in the same context, or in other words, the same network (Chi et al., 2010).

A typical pattern of competition, depicted in Figure 1, is consisted of initializing a strategic move, competitors' denial, strategy matching and counterattack. When the initializing firm does not initialize a follow up move by the time of the counterattack, it will lose the strategic control to its one of its competitors (MacMillan, 1988). These attacks are competitive actions, which we will later define.

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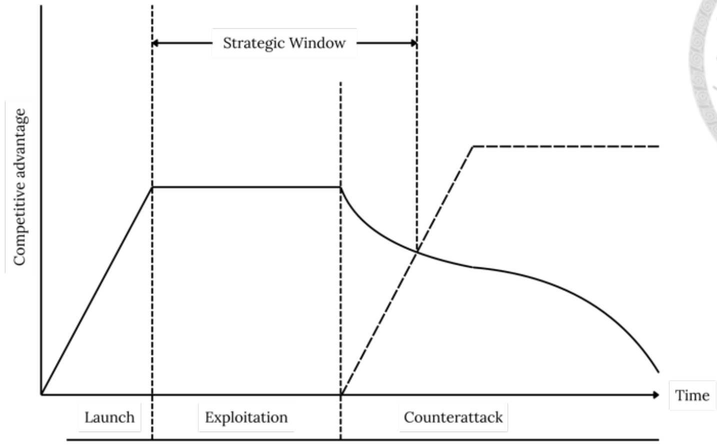

Figure 1 Dynamics of strategic moves (MacMillan, 1988)

Once a competitive action is initiated, it is important for other rivalry firms to react swiftly and update their strategies in order to maintain their positions in the market (Derfus et al., 2008; Kim et al., 2018). On one hand, by performing a matching counteraction to a competitive action initiated by a rival, a firm can share in the above-normal economic profits (Wei et al., 2015). Debruyne et al. (2002) even states the consequence of losing market share if firms consistently fail to react with useful counteractions. Such pressure drives decision-makers to make counteractions (MacMillan, 1988; Yang & Meyer, 2015), which then result in a contiguous competitive cycle over time. Given companies being likely to respond to competition (Barnett & Hansen, 1996), what and how should the response be? On one hand, to prevent a firm from falling behind competition, it is vital to recognize competitive dynamics and develop appropriate counteractions accordingly. On the other hand, a firm should benefit from accurately predicting future actions its competitors tend to take to get a head start over

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them (Tej Adidam et al., 2012; Wright et al., 2002). Business interactions are getting increasingly complex, hence the need for the adoption of advanced inter-firm competitive action analysis methods. These tasks can obviously be done leveraging third party advisories, it is nonetheless often time consuming and incurs significant costs.

Competitive action prediction is beneficial for three types of players in the market. We should note that competitive action prediction (CAP) is not designed to assist firms in forecasting their own actions, instead, it is viewed as beneficial for the three types of players in the market. For a firm in the competitive landscape, a firm can take initiative and seize potential first mover advantage if the future actions of its competitors are accurately anticipated. Investors can assess market risks and opportunities more effectively with advanced knowledge into competitive dynamics. Third party advisors can provide clients additional insights along with proposing counter moves accordingly. Nevertheless, a notable research gap within the domain of competitive action prediction still exists.

1.2. Research motivation

The business world nowadays is increasingly fast paced, and it is critical to consider external relations when making strategic decisions in such uncertain environments (Bettis & Hitt, 1995; Dishman & Calof, 2008). However, “profiling competitors’ past behavior can be difficult; predicting competitors’ future behavior is much more difficult. Predicting

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competitors' future behavior that is a response to any particular action of the focal firm is doubly difficult." (Montgomery et al., 2005) Undoubtedly, it is challenging to predict competitors' competitive actions, from both the strategic and practical point of view. While business executives frequently considered internal factors and customer information in their strategic decisions, less than 10% contemplated future competitor behavior or reactions, indicating a significant oversight of the competitive landscape in their decision-making process (Montgomery et al., 2005). According to a survey conducted among business managers, 86-96% of participants believe competitors exhibit surprising behavior occasionally across thirteen strategic categories; over half of the respondents estimate this occurs at least half of the time (Horn, 2023). From an investor point of view, the obstacle lies on information collection and consolidation; for third party advisors, though possessing expertise in analysis, doing such due diligence is also costly.

A data-driven, automatic, and scalable method for CAP is hence proposed. We view competitive action prediction through the lenses of competitive dynamics. When we compare competitive dynamics with the well-known Five Forces Analysis (Porter, 1980), the perspective of competitive dynamics is of higher granularity. Studies with this perspective are action based, i.e., perform firm and action level analysis instead of industry level analysis. They mainly use repertoires of actions as competitive strategies instead of generic types, providing a more thorough view of strategy. The *dynamic* aspect

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of competitive dynamics refers to the exchange of interactive moves between two firms (Chen & Miller, 2012).

Competitive actions are found to correlate with firm performance. For example, a positive effect of alliance network density on action volume was discovered when automakers have a high level of IT-enabled capability (Chi et al., 2010). Some competitive dynamics-based studies investigate the complexity of competitive actions and their correlations between firm growth in terms of knowledge, market share and return on assets (ROA) (Larrañeta et al., 2014; Ndofor et al., 2011; Thatchenkery et al., 2012). Turner et al. (2022), on the other hand, suggested that repertoire complexity will eventually reach a point where there are diminishing returns.

Competitive dynamics is already widely used for a firm to examine its external relations; many researchers have touched on analyzing competitive dynamics. While some try to (a) propose frameworks/tools for external analysis, others work on (b) investigating existing practices. Prevailing frameworks like the TOWS Matrix (Weihrich, 1982), the Strategic Position and Action Evaluation (SPACE) Matrix (Radder & Louw, 1998), the Growth Share Matrix, i.e., the BCG Matrix (Henderson, 1970) can be attributed to the first category, and real world examples and case studies lie in the second category, such as Deng et al. (2000) performing a multi-criteria analysis to the inter-firm comparison problem to a firm in Wuhan, China.

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The aforementioned matrix-like tools and case studies focus on the attributes of the competitive landscape. CAP offers an additional perspective by proposing a data-driven analysis at the action level, which complements the existing tools and case studies used in decision making.

1.3. Research objective

This study delivers competitive action profiling, competitor identification and CAP leveraging public news data. Taking historical news data as input, the pipeline we propose identifies competitive actions from text data, aggregates events accordingly, selects competitors and makes forecasts about the frequencies of different competitive actions in the future. We ask:

- How do different methods of identifying competitors affect the prediction process?
- How do different prediction models perform when predicting competitive actions?

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2. Related Work

2.1. Competitive dynamics and competitive actions: definition and typologies

We follow Joel and Korn (1996) and define competitive dynamics as the study of how rival firms compete through specific actions within their strategic contexts. It is clear that competitive actions of a firm, serving as the foundation of competition, are regarded as the primary focus of research in competitive dynamics. Moreover, relativity is also critical. A firm's strategy and market position should be looked at in relation to its competitors' strategies and positions.

According to Smith et al. (1991), one of the earliest studies in the field of competitive dynamics, a competitive action is a specific and detectable move that can improve or defend the firm's competitive position. More specifically, competitive actions refer to actions a firm takes to maintain or enhance market position by raising the value of its products and services (Andrevski et al., 2016), leading to temporary advantages over other competitors (Wei et al., 2015). Kim et al. (2018) also states that firms that use competitive actions such as new product introduction, marketing, and capacity expansion can show how aggressive they are searching for new ways to satisfy its customers.

In previous literature, different typologies of competitive actions were proposed. One part of the literature proposed generic categories of competitive actions, as listed in Table 1.

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Table 1 Typologies of competitive actions

Study	Typology
Ferrier et al. (1999)	▪ major new pricing actions ▪ new marketing and promotional actions ▪ new products ▪ new capacity additions ▪ new legal actions ▪ new signaling actions
Donald Hopkins (2003)	▪ outsourcing ▪ pricing/marketing ▪ manufacturing ▪ JV and restructuring ▪ geographic expansion ▪ government/legal ▪ new technology/product/features/distribution methods
Smith et al. (2005)	▪ pricing actions ▪ marketing actions ▪ new product actions ▪ capacity-related actions ▪ scale-related actions ▪ service and operations actions ▪ signaling actions
Yu and Cannella Jr (2007)	▪ capacity action ▪ major product action ▪ minor product action ▪ pricing action ▪ marketing action ▪ distributional/service improvement action
Chi et al. (2010)	▪ pricing ▪ marketing ▪ product improvements ▪ new product versions

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	▪ new product introductions ▪ market expansion
Qi et al. (2023)	▪ marketing action ▪ product R&D ▪ pricing and earnings ▪ legal action ▪ signaling action ▪ capacity action ▪ service action

Following prior effort mentioned above, Table 2 demonstrates our proposed typology of competitive actions. This typology incorporates the generic topologies in Ferrier et al. (1999), Smith et al. (2005) and Qi et al. (2023). Furthermore, as we focus on the airline industry, the studies that proposed airline-specific actions also shed light on defining and distinguishing particular actions.

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Table 2 Proposed typology of competitive actions

Action	Description	Examples in the airline context
Pricing	Changing in price (either raise or discount)	price cut (Chen & Miller, 2012; Kwoka & Batkeyev, 2019), change in fare structure (Chen & Hambrick, 1995)
Marketing	Campaigns to advertise, promote and communicate certain values with customers	(special) promotion (Smith et al., 1991), co-promotion with non-airlines, frequent flyer programs (Chen & Miller, 1994), loyalty building (Kwoka & Batkeyev, 2019)
Product introductions and improvements	Launch of new products or enhancements to existing ones, aimed at improving quality or functionality	new service, service improvement (Chen & Miller, 1994)
Market expansion	Entering new geographical markets	hub creation and major expansion, entry into new route (Chen & Miller, 1994; Smith et al., 1991)
Capacity improvements	Increasing the capability of a facility or system to meet growing demand and/or improve efficiency.	increase/decrease in daily departures (Chen & Miller, 1994), purchasing new aircraft (Miller & Chen, 1994)
Legal action	Dispute resolving and rights enforcing by the legal system, including but not limited to litigations, arbitration, appeals, etc	lawsuits with other airlines or governments
Outsourcing and alliance	contracting tasks or functions to external parties or forming cooperative partnerships with other organizations	feeder alliance with a commuter airline, cooperation with other airlines, co-promotion with non-airlines (Chen & Miller, 1994)

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Merger & acquisition and finance investments	Consolidating firms by mergers and acquisitions and gaining ownership stakes by finance investments	merger and acquisition, purchasing stake of other airlines (Chen & Miller, 1994)

2.2. Methods for competitive actions profiling

Profiling competitive actions has been a labor-intensive task and occurred to be hard to scale up. Mostly using news articles, researchers in the past exerted a lot of effort in scanning the articles, locating competitive actions, and then categorizing them. Chen et al. (1992) was the first to propose a semi-automated approach to identify competitive actions from news articles. They then used key terms such as "in responding to" and "under the pressure of" to mark the occurrence of responding competitive actions. 191 actions were identified using this method. Young et al. (1996) identified a total of 1,903 rivalrous actions in the computer software industry with a similar method with Chen et al. (1992). Ferrier et al. (1999) applied a keyword-based annotator to the headlines and abstracts of published news reports. They consequently obtained over four thousand distinct actions, which were then manually categorized according to their aforementioned typology. Rindova et al. (2010) looked into firms relevant to the commercialization of the Internet in the mid-1990s. They collected the press releases of forty firms as they believed that action announcements received more investor responses than action implementation. Their manual coding of the press releases yielded 2,087 actions, which were then

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categorized into eight general types. Nicolau-Gonzálbez and Ruiz-Moreno (2014) took a similar path and collected about 200 news articles from the finance field. They manually profiled the articles and identified 126 actions in total, including "geographical expansion" and "launch of new products." Wei et al. (2015) collected news about 72 Chinese firms over a five-year period with predefined queries and had experts annotate the articles, resulting in 3,956 actions, either market or non-market related. They proposed a typology of ten market-related action types. The methods introduced in said studies required experts or trained annotators, resulting in low profiling efficiency and relatively high costs.

To our knowledge, no prior research has focused on automatically profiling competitive actions, especially within a supervised learning framework. Additionally, there are no studies that used automatically profiled actions for downstream tasks.

It is noteworthy that profiling actions is not simply a classification task, especially as we use news articles as the main source. The researchers of Chen et al. (1992) not only extracted actions from articles, they *painstakingly* traced action sequences backwards to group up articles featuring the same action. Nicolau-Gonzálbez and Ruiz-Moreno (2014) also looked for news articles with the initial action to find the primary actor and respondents in a temporal order. This being said, it is necessary for us to incorporate event detection and document classification while performing the profiling task.

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2.3. Competitive actions prediction

Few studies tackle competitive actions prediction. While most existing work examines factors influencing competitive actions characteristics, with few studies attempting to predict these actions. There are two main paths previous studies take to predict competitive actions in the literature, namely explanatory models or data mining methods. A set of studies dig deeper by discovering predictors of the characteristics of a firm's competitive repertoire (Miller & Chen, 1994), which stands for the set of actions it takes during competition. Another two studies apply data mining methods to the prediction task.

Several prior studies on competitive actions prediction incorporate explanatory models and aim for predicting the characteristics of a firm's competitive repertoire. Studying the airline industry, Chen and MacMillan (1992) revealed the likelihood of a defender responding to an attacker's action increases with the defender's dependence on its market, particularly when the action involves a price change. The study also predicted the likelihood of nonresponse using factors such as competitor dependence and action irreversibility; the former has a negative effect while the latter has a positive impact on the likelihood of nonresponse. Ferrier (2001) used top management team heterogeneity, past performance, organizational slack and industry environment to predict the volume and duration of competitive actions. The study found that these predictors significantly

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impacted the duration of competitive actions; however, they did not exhibit significant predictive power regarding the volume of such actions. Chen et al. (2010) utilized firm market share and firm resources to predict the frequency of actions. They claim firms took more market-related actions in rivalrous situations and more R&D related actions in a growing sector.

Prior studies that apply data mining techniques on the same topic remain few. Ben Sassi et al. (2016) and its follow up study Ben Sassi et al. (2022) is the first set of research to tackle the competitive action prediction problem using data mining methods. They collected service menus from several Tunisian telecom firms. The service types are integrated with the firm attributes to form a representation for a firm-action pair. They started with performing action association, that is, to form clusters of different firm-action pairs using K-modes clustering. The clustering results are used in generating the prediction rules in their rough set rule-based prediction architecture. With these prediction rules, a firm can foresee the potential services its competitors are likely to offer. Although these studies employed K-modes clustering, they were unsupervised and did not involve time series analysis, thereby missing the dynamic aspect of competitive dynamics.

Table 3 summarizes the current literature on CAP. By and large, most studies consider the volume or complexity of competitive actions as the independent variable(s).

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In our case, the occurrences of different competitive actions are used as both the independent variables and the dependent variables.

Table 3 Overview of CAP literature

Study	**Independent variable(s)**	**Dependent variable(s)**	**Profiling method**
Chen et al. (2010)	• competitor dependence • action irreversibility • price change involvement	likelihood of competitor response	
Ferrier (2001)	• top management team heterogeneity • past performance • organizational slack • industry environment	volume and duration of competitive actions	keyword based processing
Chen et al. (2010)	• market share • firm resources	frequency of competitive actions	
Ben Sassi et al. (2016); Ben Sassi et al. (2022)	• service types • firm metadata	service types	

We argue that the explanatory models lack the ability of automatically predicting competitive actions. It is labor intensive to collect data and construct the features. Ben Sassi et al. (2016) and Ben Sassi et al. (2022) use service types as proxies for competitive actions, limiting their findings to a specific industry. They also performed a static analysis

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instead of incorporating time series in the study. We hereby propose a general end-to-end pipeline involving minimal manual work and an automated prediction model.

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3. Proposed Methodology

3.1. Problem formulation

As seen in the existing literature, studies either attempt to foresee certain characteristics of competitive actions or forecast future service types. This study intends to directly predict the competitive repertoire taking a data-mining based approach. According to studies such as Derfus et al. (2008), Kim et al. (2018), we assume a firm's competitive repertoire is likely to be affected by its main competitors, it is hence obvious to base the prediction task on successfully identifying them. On the other hand, the evolution of the competitive landscape should also be considered, leading us to utilize historical repertoires as we construct prediction models with time series data. Following this methodology, a firm is able to make predictions based on its selected breadth of the competitive landscape and depth of historical data.

Here we formulate the problem and define corresponding notations of competitive actions prediction. We have $F = \{f_1, f_2, \dots, f_n\}$ denoting the set of n firms and C denoting the set of competitive actions as listed in Section 2. A repertoire CR is represented by the accumulated number of the eight actions $c_1, c_2, \dots, c_7, c_8$ of a firm, i.e., $\mathrm{CR} = \{c_1, c_2, \dots, c_7, c_8\}$. Each competitive action repertoire of a firm f_i at timestep t is a vector of length $|C|$ and is denoted as $\mathrm{CR}_{i,t} = \{c_{1_{i,t}}, c_{2_{i,t}}, \dots, c_{7_{i,t}}, c_{8_{i,t}}\}$, where every element represents the frequency of the action performed by f_i during time period t.

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The main objective of our research is to accurately predict the competitive actions repertoire at timestep $t+1$ for a given firm f_i by leveraging its historical repertoire data along with that of its competitors (e.g., f_u and f_v) over k periods, i.e., using $\{\mathrm{CR}_{i,t}, \ldots, \mathrm{CR}_{i,t-k-1}, \mathrm{CR}_{u,t}, \ldots, \mathrm{CR}_{u,t-k-1}, \mathrm{CR}_{v,t}, \ldots, \mathrm{CR}_{v,t-k-1},\}$ to predict $\mathrm{CR}_{i,t+1}$.

Our research consists of three main modules, as depicted in Figure 2.

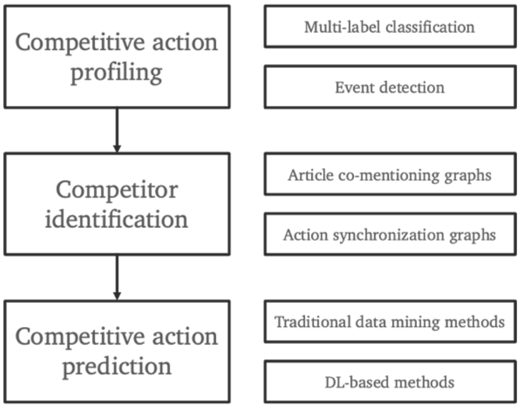

Figure 2 Three modules of our research

As shown in Figure 2, the competitive action profiling module annotates the articles with competitive actions and consolidates news articles that describe the same event. The competitor identification module is based on firm-pair co-occurrence history in terms of article co-mentioning and co-actions. Competitive repertoire prediction can be done with either traditional data mining techniques or advanced deep learning-based methods. Further details on these modules will be provided in subsequent sections.

3.2. Competitive action profiling

We base our research on news data. When a firm initiates a competitive action, this action is typically reported by multiple news outlets. Thus, utilizing news data provides

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a comprehensive and reliable means of capturing a firm's competitive repertoire. The profiling of competitive actions from news data is of two steps. We first build a supervised classification model that can extract competitive actions from unstructured text data. However, as a competitive repertoire consists of the number of actions instead of the total count of appearances in news articles, it is essential to categorize annotated news articles by events in the second step.

We begin by automatically annotating articles. Using a small portion of manually labeled data, we perform a multi-label classification task. The objective is to extract every competitive action mentioned in a given article; if no actions are mentioned, the article is labeled as "none." Using this portion, we fine-tuned several popular pretrained language models to better suit our classification task. Figure 3 demonstrates the architecture of the multi-label classifier.

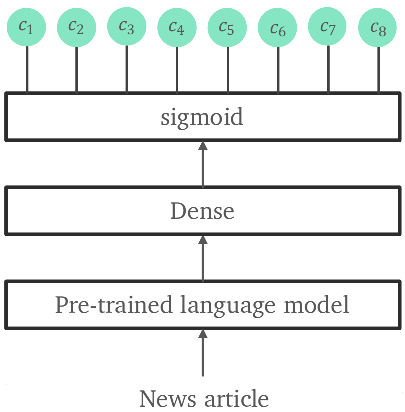

Figure 3 Architecture of the auto-profiler

The auto-profiler is built by fine-tuning several pretrained transformer-based language models on the annotated documents to fit our multi-label classification task,

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namely BERT (Devlin et al., 2018), DistilBERT (Sanh et al., 2019), XLNet (Yang et al., 2019), MPNet (Song et al., 2020) and Longformer (Beltagy et al., 2020). The architecture, as shown in Figure 3, is rather straightforward. Upon obtaining the representations of the news articles via the pre-trained language models, a dense layer is employed to apply a linear transformation to these high-dimensional embeddings. After the linear transformation, a sigmoid activation is used to output probabilities that indicate whether each label exists independently.

After obtaining the featured actions of all articles, we turn to categorizing news articles by events. Let's take a look at this sequence in Table 4 of news articles mentioning the capacity improvement of Delta Airlines as an example.

Table 4 Similar news pieces of Delta Airlines improving capacity

Firm	Title	Date	Action
Delta Airlines	Delta Air Lines Orders up to 70 Bombardier CRJ900 NextGen Jetliners	12/06/2012	Capacity improvements
	Delta orders 40 Bombardier Regional jets as it revamps its fleet	12/07/2012	
	Delta orders up to 70 Bombardier regional jets	12/07/2012	

The example illustrates that two critical factors must be considered for the successful execution of this task. First off, news articles describing the same event should exhibit similar content in terms of word usage. Moreover, news articles must be temporally close to each other. Considering these factors, we employ incremental group average clustering

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(GAC) techniques proposed by Yang et al. (1998) to detect events within the corpus. This method is applied to each firm individually, addressing one action at a time.

We denote q as the queried event and a as a news article in an ongoing event e. To measure how close (temporally) articles y and z are, we define time closeness (*TC*) as

$$TC_{y,z} = \max\left\{0, 1 - \frac{|D_y - D_z|}{60}\right\}$$

where D_y and D_z represent the date of articles y and z. Moreover, we utilize cosine similarity to represent the content proximity (*CP*) between articles y and z, denoted as

$$CP_{y,z} = \frac{\mathrm{emb}_y \cdot \mathrm{emb}_z}{|\mathrm{emb}_y||\mathrm{emb}_z|},$$

where emb_y and emb_z are the representations of the articles y and z. The similarity score between q and e is thus defined as the maximum of the product of time closeness and content proximity

$$SC_{q,e} = \max_{a \in e}\left\{TC_{q,a} \times CP_{q,a}\right\}.$$

It is noteworthy that when calculating $SC_{q,e}$, the maximum operation is employed rather than the average operation mentioned in Yang et al. (1998). In other words, we took a single-link clustering approach. This is because we believe news articles describing the same event can last long in time and might exhibit a chain-like connection. For example, a major event such as an airline merger, a regulatory change, or a significant accident can generate a continuous stream of related articles over an extended period.

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At the meantime, we also define the similarity threshold SC_θ according to the sub-corpus associated with every action. We design the clustering rule as to add q to $\max_e SC_{q,e}$ if $\max SC_{q,e} > SC_\theta$. Otherwise, we add q to a new event e'. This mechanism is designed to prune given data, allowing for a proxy of event occurrences. These events enable us to identify the main competitors for a given firm at a given period.

3.3. Competitor identification

There is extensive research on competitor identification. Chen (1996) measured market commonality and resource similarity, the two key aspects of competitive dynamics, finding out that firms with low market commonality and high resource similarity are most likely to go against each other. Ma et al. (2011) constructed graphs according to co-mentioned firms in news articles, calculated graph attributes and built classifers to determine whether competition exists between a given firm pair. It is also suggested to identify competition by measuring the covariance of cross-elasticities on a firm's demand side and the supply side (Cattani et al., 2017).

In recent years, competitor identification is also done by text mining or web mining. Yang et al. (2018) discovered that firms with patent and social media data similarity are four times more likely to be competitors. Ye et al. (2022) made use of online reviews alongside popular data mining methods KNN and LDA to determine competitors in the hotel industry.

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Among the market commonality and resource similarity aspects (Chen, 1996), we leverage the news articles in two ways: article co-mentioning and co-action of firms.

3.3.1. Co-mention graphs

Let us first examine the article co-mention graph(s). We assume that competing firms in a same industry will be co-mentioned in news articles, following Ma et al. (2011). Take the following snippet retrieved from the 2013 article titled "Retaliation? United adds flights to Delta hubs" as an example.

United Airlines is adding new routes to the key hubs of one of its biggest rivals. Starting April 1, United will add nonstop flights between San Francisco and Atlanta and between Los Angeles and Minneapolis/St. Paul. The carrier will fly two daily round-trip flights on each route. Perhaps not coincidentally, United's new routes come just a week after Delta announced plans for a new route connecting Seattle and San Francisco. Delta also announced plans to grow its schedule in Seattle, a move that included increasing flights to Los Angeles – another of United's hubs. [1]

Given a set of news articles, these graphs record the co-occurrences of firms in an article during a certain timestamp, e.g., a year.

We let $art\text{-}M^t$ denote a square matrix of order n, representing the co-occurrence

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[1] Ben Mutzabaugh, *Retaliation? United adds flights to Delta hubs*, https://www.usatoday.com/story/todayinthesky/2013/10/07/retaliation-united-adds-flights-to-delta-hubs/2935925/

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of firms in news articles during timestamp t. Each element $art\text{-}M_{i,j}^{t}$ of the matrix represents the number of articles in which firms f_i and f_j co-occur during period t (in our case, half a year). This co-occurrence matrix is symmetric, i.e., $art\text{-}M_{i,j}^{t} = art\text{-}M_{j,i}^{t}$, reflecting the reciprocal nature of co-occurrence. In the article snippet shown above, other than the originally queried "United Airlines," we also spotted Delta Airlines, confirming for us how these big airline firms from the US are in competition with each other. Hence, we increment $art\text{-}M_{i,j}^{2023}$ and $art\text{-}M_{j,i}^{2023}$, where $i, j \in$ {Delta Airlines, United Airlines} and $i \neq j$.

3.3.2. Co-action graphs

Following this line, we also build a set of action co-occurrence graphs. Given a target firm f_i and its corresponding action C_g, $g \in \{1,2, \ldots ,7,8\}$ during timestep t, we look for firms that have performed the same action C_g within a time interval d. Let $act\text{-}M^{t}$ denote a square matrix of order n, representing the action co-occurrence of firms during timestamp t. Each element $act\text{-}M_{i,u}^{t}$ of the matrix means the number of co-occurring actions firms f_i and f_u have taken within time period t (half a year). This is also symmetric. For example, if China Airlines and EVA Air both took the action of "capacity improvements" within a gap of $d = 14$ days, we increment $act\text{-}M_{i,u}^{t}$ and $act\text{-}M_{u,i}^{t}$ where f_i represents China Airlines and EVA Air is represented by f_u.

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Given the article co-mentioning and co-action graphs, we are able to find the top α competitors of firm f_i by the following steps. Here we utilize article co-mentioning graphs as an example in the following notations, although the same mechanism applies to the co-action graphs. Let σ be a permutation of $\{1,2,\ldots,n\}$ that sorts the elements of $\mathbf{r}_i$, the i^{th} row vector from the matrix art-M^t, in descending order.

$$\mathbf{r}_i^{\sigma} = \left[art\text{-}M_{i,\sigma(1)}^t, art\text{-}M_{i,\sigma(2)}^t, \ldots, art\text{-}M_{i,\sigma(n)}^t\right], art\text{-}M_{i,\sigma(1)}^t \geq art\text{-}M_{i,\sigma(2)}^t \geq \cdots \geq art\text{-}M_{i,\sigma(n)}^t \quad (3.4)$$

The indices of the top α columns in row i are given by the first α elements of the permutation σ:

$$\text{top}_{\alpha}(\mathbf{r}_i) = \{\sigma(1), \sigma(2), \ldots, \sigma(\alpha)\}.$$

Firms $f_x, x \in \{\text{top}_{\alpha}(\mathbf{r}_i)\}$ are then considered as the main competitors of f_i. The same mechanism is applied to the action co-occurrence graphs. In our study, α is set to 2 and k is set to 3, i.e., we focus on two major competitors over 3 periods for a firm.

3.4. Competitive action prediction

We first propose an RNN-based time series prediction method that predicts the competitive repertoire of firm, as depicted in Figure 4, hereinafter referred to as the CAP (GRU+Attn) model. Inspired by Li et al. (2019), we use attention mechanisms to enhance GRU by better selecting and encoding important input sequences, improving long-term dependency handling.

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Figure 4 shows the architecture of the proposed CAP (GRU+Attn) model. To start off, for firm i at period p, given its competitors at said period, e.g., firms u and v, we ought to construct its feature vector of repertoires $H_{i,p}$ as the input. We extract the competitive repertoire of firm i at period p $\mathrm{CR}_{i,p}$, as well as the competitive repertoire of firms u and v at period p, $\mathrm{CR}_{u,p}$ and $\mathrm{CR}_{v,p}$. To predict a firm's competitive repertoire at period $t+1$, we collect the feature vectors from k periods, i.e., from period $t-(k+1)$ to t.

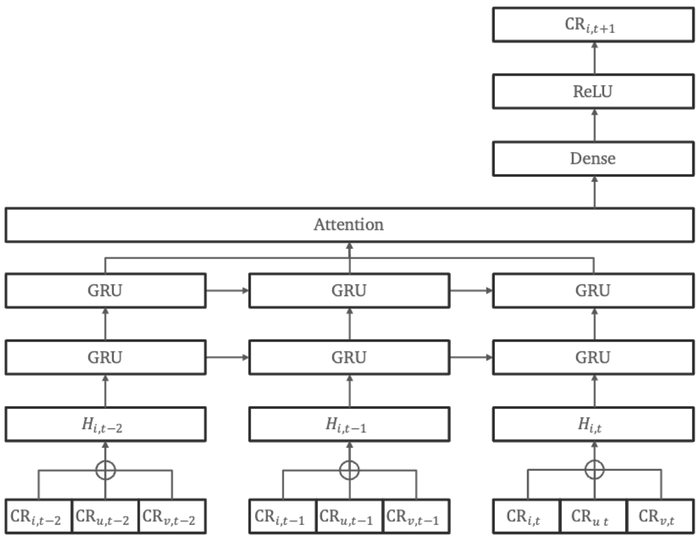

Figure 4 The proposed CAP model

The GRU layers perform feature expansion and abstraction. With 24 features given as input, the first layer and second layer extracts 64 and 48 features respectively. The attention layer weighs the importance of different time steps dynamically. Eventually, the dense layer outputs the predicted frequencies of all eight actions at the next period utilizing a rectified linear unit (ReLU) activation function.

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4. Experiments

4.1. Introduction of target industry: the airlines industry

In this study, we target our experiments on the airlines industry as it is highly competitive. Many studies on competitive dynamics have targeted this industry, such as Smith et al. (1991), Miller and Chen (1994), Chen and Hambrick (1995), Chen (1996), Chen and Miller (2012), Hannigan et al. (2015) and so on. The industry is targeted for several reasons.

On the industry level, firms in the airline industry can be very similar in terms of price, customer pool, service quality, etc (Chen, 1996). Airlines serve clearly defined but highly similar markets, and such overlap intensifies the industry (Hannigan et al., 2015). With price being a decisive factor, there has been a continuous downward trend with a compound annual decline rate of -8.18% in median fares from 2013 through 2019, before the pandemic hit (Sun et al., 2024).

On the firm level, even the textbook firm Southwest is struggling. Southwest Airlines was regarded with financial envy by the airline industry for decades. Prior to the pandemic, Southwest had never filed for bankruptcy and enjoyed 47 straight years of profitability. The prosperity has several reasons, including coming up with low fares in air travel and offering free changing or cancelling. They promoted affordability and simplicity by streamlining air travel with only one type of ticket and no pre-arranged seating.

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However, most airlines today also offer basic fares with minimal amenities. They then charge for seating and checked bags, thereby generating significant additional revenue. At the meantime, its competitors keep improving their products (e.g., luxurious business class seats, newer airplanes) that Southwest doesn't even offer. Such market trend resulted in a disappointing report in Q1 2024, triggering Southwest to consider making changes to the seating and boarding process (Knutson & Sider, 2024). From our perspective, had Southwest accurately predicted its competitors' moves, it could have taken counteractions in advance instead of rethinking its strategy after a revenue decline.

On the data availability level, the airline industry is advantageous due to its abundance of accessible data. Air travel plays a significant role in the daily lives of many people, making it a frequent topic in news articles worldwide. For instance, consider these example headlines in Table 5 that appeared within just two months—clearly demonstrating the extensive public data available for analysis.

Table 5 Example headlines of airline news

Title	**Source**
How Delta made itself America's luxury airline — and what United wants to do about it	CNBC Jun. 25, 2024
Alaska Airlines loses appeal in $160 million UK trademark dispute with Virgin Aviation	Reuters Jun. 11, 2024
JetBlue and Spirit Have More Bad News to Face: A Very Active Hurricane Season	Barron's May 25, 2024
Spirit Airlines gets rid of change and cancellation fees, joining Frontier	CNBC May 21, 2024

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4.2. Dataset

In this section, the real-world dataset used in this paper is introduced. To obtain a pool of airline firms, we queried the COMPUSTAT database using the Standard Industrial Classification (SIC) code 4512 for the airline industry to obtain a pool of airline firms. The initial list of firms was then sorted by their average revenue over the period from 2011 to 2023, resulting in an updated list of the top 45 revenue-generating firms in the industry. A snippet of the top 20 firms is shown in Table 6. In our study, we treat Air France and Royal Dutch Airlines as distinct entities, even though they belong to the same venture in COMPUSTAT. Similarly, British Airways and Iberia are considered separate companies.

Table 6 Snippet of top-ranking airlines by revenue

Airline	**Avg. Revenue in USD (M)**	**Airline**	**Avg. Revenue in USD (M)**
Delta Airlines	39890.46	Air China	13705.26
United Airlines	37439.54	China Eastern Airlines	11444.97
American Airlines	36992.54	Qatar Airways	11399.14
Air France	25734.95*	Cathay Pacific Airways	11273.37
Royal Dutch Airlines	25734.95*	All Nippon Airways	10630.50
Lufthansa	25308.86	Singapore Airlines	10507.96
Emirates Airlines	25157.14	LATAM Airlines	9111.09
British Airways	20069.26*	Qantas Airways	8877.76
Iberia	20069.26*	Korean Airlines	8805.36
Southwest Airlines	19218.46	Japan Airlines	7709.12
China Southern Airlines	15131.00	Alaska Air	6586.75

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These 45 firms were selected as the focus of our study. To gather data on the competitive actions of these airline firms, we utilized Google News, a public global news hub. [2] Google News was queried with the name of each airline firm to collect up to 50 articles per month for each firm from 2011 through 2023. Only English-language articles were collected. Figure 5 depicts the distribution of average articles retrieved per month.

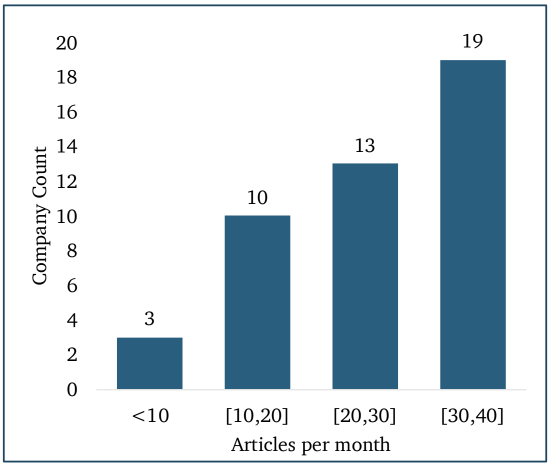

Figure 5 Distribution of average articles retrieved

A total of 194,766 articles were retrieved for analysis. From these articles, we figure there occurred to be three main categories of sources in the source material: mainstream news media (e.g., CNN, The Guardian), business-focused publications (e.g., Business Insider), and specialized aviation outlets (e.g., The Points Guy, Aviation Week). On average, for a firm, approximately 25.4 articles are retrieved for a firm per month and 300.8 for a year. The distribution of articles per firm per year is depicted in Figure 6.

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[2] https://news.google.com/home?cf=all&pz=1&topic=n&hl=en-US&gl=US&ceid=US:en

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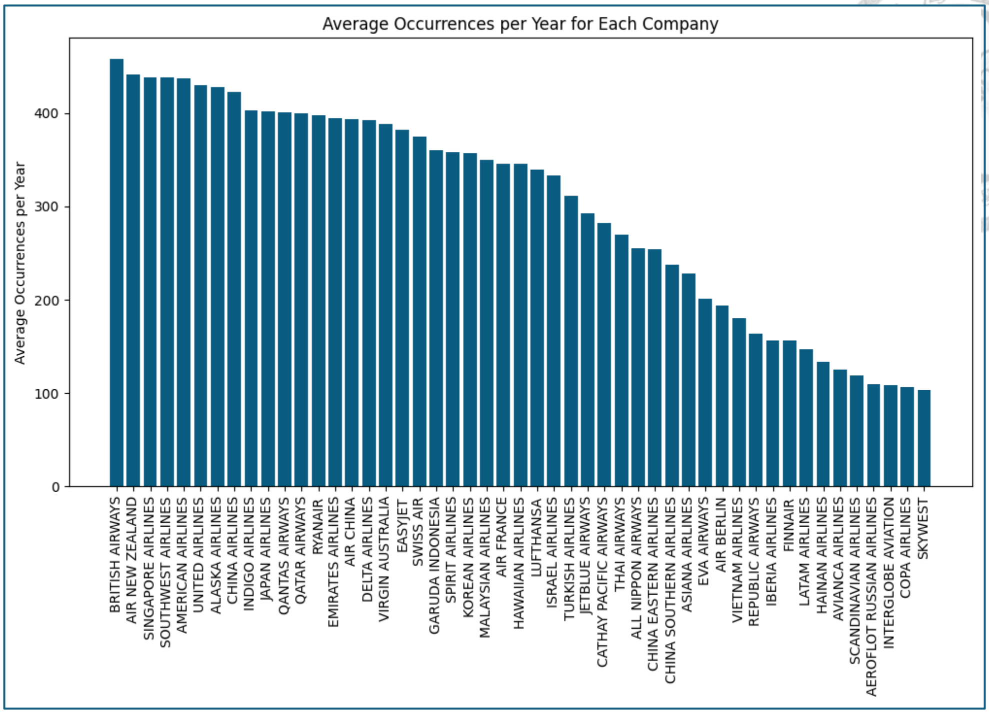

Figure 6 Average occurrences per year for every firm

Given raw news data, it is obvious for us to perform necessary preprocessing. We start with applying a rule-based approach to discard redundant articles. A two-step data cleansing process is developed to remove articles mentioning none/too many of our target firms. First, if an article does not mention any airline in the firm pool, it is viewed as irrelevant and will be removed. For airlines with easily confusing names, we adjusted their queries accordingly: for example, ANA was changed to All Nippon Airways, and SAS was transformed to Scandinavian Airlines. We apply a strict string-matching mechanism to our articles. If no matches are found, the article is discarded. Next, from the remaining articles, we eliminate those that are general industry reviews, which often mention too many airline firms. Specifically, we identified the 95th percentile for the

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number of firms mentioned per article, which was six in our case, and classified these articles as general reviews. Consequently, these articles were also discarded.

With this filter applied, the remaining 117,889 articles form the *airline dataset*. We consequently move on to finding the main featured firm in a given article. As manually finding the main featuring firm in articles is exceedingly labor intensive, a rule-based article filter therefore built. This filter follows the following rules in a sequential manner:

Rule 1: If one and only one firm exists in the article title, assign the article to the firm.

Rule 2: If not, assign the article to the firm most mentioned.

Rule 3: If a tie occurs, the article is assigned to the firm mentioned first.

We annotated 2,400 articles with the competitive actions featured in the articles. If there exist no competitive actions, the article is labeled "none". The distribution of labels is shown in Figures 7 and 8.

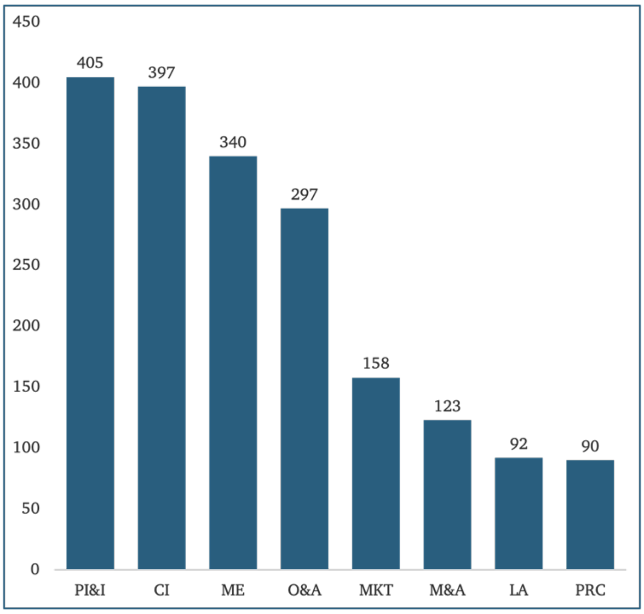

Figure 7 Action distribution of labeled data

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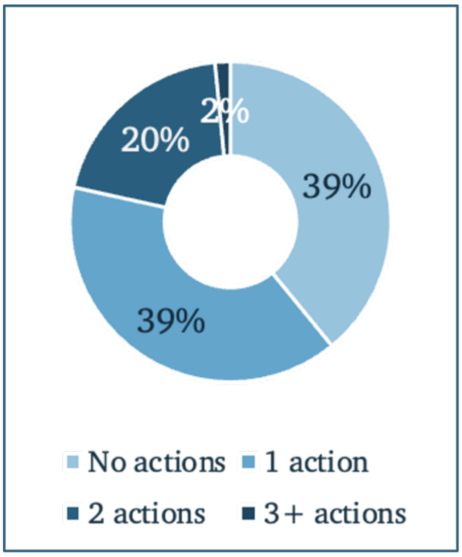

Figure 8 Action count distribution of labeled data

4.3. Experimental setup

4.3.1. Competitive actions profiling

For every article, the dense layer takes the 768-dimension output of the language model as input and outputs a vector with dimension 256. We trained the model for 45 epochs with the learning rate set to 9e-5. The results, shown in Table 7, are the averaged of precision, recall and F_1 scores across all eight actions.

Table 7 Auto-profiler performances

Method	Precision	Recall	F_1
BERT	0.81	0.89	0.85
DistilBERT	0.89	0.91	0.90
MPNet	0.87	0.91	0.89
Longformer	0.82	0.90	0.85
XLNet	0.91	0.92	0.92

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Considering classification performance and computational intensity, the fine-tuned version of XLNet was utilized to inference the remaining unlabeled documents in the airline dataset.

For every action, we ought to define the similarity thresholds SC_{θ} according to the sub-corpus associated with it. Several models such as the vector space model, BERT-based models and XLNet were selected to represent the 117k+ articles. Given the representations of the articles, we calculate the pairwise similarities between the articles in the sub-corpus of an action and set the value at the 15th percentile as the threshold SC_{θ}. Table 8 demonstrates the average SC_{θ} of all eight actions with different thresholds $(P_{15}, P_{25}, P_{50}, P_{75})$ by the aforementioned representation methods.

Table 8 Average SC_{θ} among eight actions with different thresholds by representation

Representation	$\boldsymbol{P_{15}}$	$\boldsymbol{P_{25}}$	$\boldsymbol{P_{50}}$	$\boldsymbol{P_{75}}$
DistilBERT	0.9175	0.9349	0.9485	0.9602
XLNet	0.8284	0.8709	0.9150	0.9390
Tf-idf	0.2388	0.2768	0.3526	0.4360

Among the models we used, tf-idf representations performed surprisingly well when distinguishing events. Representations using BERT-based/XLNet models were incapable of distinguishing articles in our collection. The difference in performance can be attributed to the nature of these representations and their sensitivity to the specific content of the articles. Since tf-idf focuses on the importance of individual terms in a document relative to the corpus, it is better at distinguishing between articles with different

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vocabularies, leading to more meaningful cosine similarity scores. On the other hand, BERT and XLNet, as they excel at understanding the context, the models often produce high similarity scores even for documents with different specific content but similar overall themes or contexts. Therefore, using tf-idf in this similarity-based event detection case proved to be more effective. After merging news articles by event clusters, the airline dataset shrunk to 6,288 events.

The observed mean occurrences in Table 9 demonstrates reasonable clustering results, but some significant players (based on events) still exist.

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Table 9 Average occurrence per year and major players by event

	Mean	Leading Firm	#	Second Leading Firm	#	Thrid Leading Firm	#
capacity improvements	3.4	British Airways	5.1	Emirates Airlines	5.1	American Airlines	4.9
legal action	1.6	Delta Airlines	5.5	Ryanair	4.9	American Airlines	4.8
market expansion	3.7	Copa Airlines	5.5	easyJet	5.1	Iberia Airlines	5.0
marketing	2.3	Hawaiian Airlines	5.1	Southwest Airlines	4.8	Alaska Airlines	4.7
M&A and finance investments	0.9	Delta Airlines	3.2	Ryanair	2.8	Lufthansa	2.7
outsourcing and alliance	3.5	Qantas Airways	6.1	Turkish Airlines	5.6	Delta Airlines	5.5
pricing	1.0	Indigo Airlines	4.4	Ryanair	3.6	Delta Airlines	3.1
product introductions and improvements	3.9	American Airlines	6.7	Finnair	6.5	Alaska Airlines	6.3

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4.3.2. Competitor identification

With a well-pruned airline dataset, we employ a six-month window size for the construction of the article co-mention and co-action graphs, with the window shifting by one month at each iteration.

Table 10 Main competitors (co-mention)

Firm	Period	Main Competitor #1	Main Competitor #2
Delta Airlines	13H1	American Airlines	Southwest
	13H2	American Airlines	Jetblue Airways
	14H1	American Airlines	United Airlines
	14H2	United Airlines	American Airlines
Singapore Airlines	13H1	Indigo Airways	Lufthansa
	13H2	Cathay Pacific Airways	Air France
	14H1	Air New Zealand	Royal Dutch Airlines
	14H2	United Airlines	Emirates Airlines

Table 11 Main competitors (co-action)

Firm	Period	Main Competitor #1	Main Competitor #2
Delta Airlines	13H1	Qantas Airways	easyJet
	13H2	Indigo Airways	United Airlines
	14H1	Air France	United Airlines
	14H2	United Airlines	Lufthansa
Singapore Airlines	13H1	Qantas Airways	Aeroflot
	13H2	Qantas Airways	Cathay Pacific Airways
	14H1	Air New Zealand	Aeroflot
	14H2	Indigo Airways	United Airlines

For the target firm f_i at period t, we extract $\alpha = 2$ firms as its main competitors according to article co-mentioning. Furthermore, for f_i at period t, we also extract $\alpha = 2$ firms as its main competitors according to co-action. The time interval in this case is

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$d = 60$ days. Table 10 and Table 11 demonstrate competitor identification examples with Delta Airlines and Singapore Airlines.

4.3.3. Competitive action prediction

After identifying competitors, we can now form the training and testing set for the competitive action prediction models. We retrieve the competitive repertoire of the competing firms to form samples. Every sample consists of four sequences: the history sequences $H_{i,t-2}$, $H_{i,t-1}$, $H_{i,t}$ and $H_{i,t+1}$ that includes the target to predict $\mathrm{CR}_{i,t+1}$. We utilize a sliding window approach with these temporal sequences. Each sequence represents a 6-month period, the model predicts the fourth sequence based on three preceding sequences. The window shift is set to 1 month, allowing for overlapping sequences to maximize utilization of available data. Samples within the range of 2011 to 2020 are used as the training set, the rest are used as the testing set, resulting in 120 for training and 15 for testing.

To train the CAP (GRU+Attn) model, the input size is set to $(3,24)$, which represents the 3 periods the model refers to and the 24 features per period. The first and second GRU layer transform the input data and output 64 and 48 features per period respectively. When the attention layer is used, the output of the second GRU is utilized as the query, key and value matrix. The attention layer provides an output of shape $(3,48)$ as well. After a suitable activation function, we extract the final state of the output. The

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models are trained for 150 epochs, the initial values of the recurrent kernel weights are set to zeros, and the initial learning rate is set to 3.5e-5.

4.4. Evaluation metrics

We use the mean absolute error (MAE) and root mean squared error (RMSE) to evaluate the quality of our numerical prediction. A brief description of the error functions and their formulae are as follows, note that $\hat{y}_i$ is the predicted value and y_i is the ground truth.

- MAE is the average over the absolute differences between predicted values and actual values, and can be calculated as

$$\mathrm{MAE} = \frac{1}{8}\sum_{i=1}^{8} |\hat{y}_i - y_i|$$

- RMSE also measures the average magnitude of the error, but it gives a relatively high weight to large errors, which makes it useful when large errors are particularly undesirable. RMSE is calculated as

$$\mathrm{RMSE} = \left[\frac{1}{8}\sum_{i=1}^{8} (\hat{y}_i - y_i)^2\right]^{1/2}$$

4.5. Baselines

We compare our model with two groups of time series prediction methods, including statistical methods and deep learning-based methods. Several representative methods are selected as baselines, which we will introduce below.

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The statistical methods include simple moving average, autoregression, and vector autoregression.

Historical Average (HA): This method predicts competitive actions by calculating the average frequency of past actions across all observed periods.

Moving Average (MA): This is calculated by taking the arithmetic mean of a given set of values over a specified number of periods.

Autoregression (AR): an autoregression model is a type of time series model where the current value of a variable is linearly dependent on its previous values. In an autoregressive model of order τ, the current value y_τ can be modeled as a linear combination of the past τ values plus an error term.

Vector Autoregression (VAR): a vector autoregression model is an extension of the autoregression model by using multivariate time series data. Each variable is modeled as a linear combination

4.6. Results

Our experiments demonstrate that leveraging GRU and Attention together, which captures temporal weights, enhances prediction accuracy compared to lazy learners and regression-based methods, as shown in Table 12. Furthermore, utilizing co-action to identify competitors results in lower errors, demonstrating that this approach more accurately models the competitive landscape.

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Table 12 Performance of CAP compared with baselines

	MAE		RMSE	
	Co-mention	Co-action	Co-mention	Co-action
HA	1.3078		1.6591	
MA	1.0572		1.3381	
AR	1.0689		1.3346	
VAR	1.2203	0.9798	1.5920	1.2375
CAP (w/o competitors)	0.8818	0.8043	1.0926	1.0852
CAP	0.8884	**0.8001**	1.0998	**0.9865**

4.7. Additional experiments

4.7.1. Additional experiment 1: Ablation test

We also experimented using only the GRU/Attention layers from our CAP (GRU+Attn) model. Table 13 shows that although using Attention solely outperforms using GRU solely, both experiments underperformed CAP (GRU+Attn).

Table 13 Performance of model variants

	MAE		RMSE	
	Co-mention	Co-action	Co-mention	Co-action
CAP	0.8884	0.8001	1.0998	0.9865
CAP (GRU only)	0.9107	0.8208	1.1200	1.0105
CAP (Attn only)	0.9924	0.9475	1.2170	1.1580

4.7.2. Additional experiment 2: Predicting action existence

Additionally, we can also extend our model to predict the existence competitive actions. Figure 9 demonstrates the slightly changed CAP model that performs this task. The activation function is changed to sigmoid while the rest remains the same. For this binary classification experiment, we use precision, recall, F_1 score and accuracy as

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metrics to evaluate the classification quality. A brief description of these metrics and their formulae are as follows. Note that TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

- Precision, the ratio of correctly predicted positive observations to the total number of positive observations, can be calculated as $\frac{\mathrm{TP}}{\mathrm{TP+FP}}$.
- Recall, the ratio of correctly predicted positive observations to the total count of actual positives, can be calculated as $\frac{\mathrm{TP}}{\mathrm{TP+FN}}$.
- F_1 is the harmonic mean of precision and recall, and is calculated as $2 \times \frac{\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}}$.

Accuracy measures the ratio of correct predictions to the total count of predictions, and is calculated as $\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$.

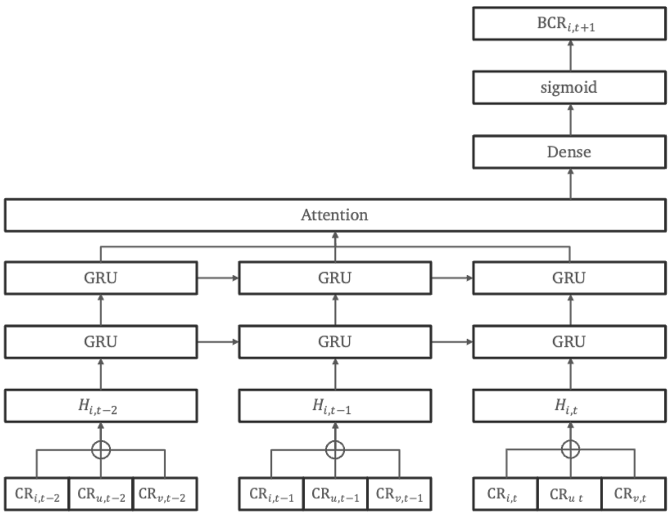

Figure 9 The modified CAP architecture for binary prediction

The prediction results form the binary competitive repertoire, denoted as $\mathrm{BCR}_{i,t+1}$, indicating which actions exist in the target period t.

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Table 14 Performance of deep learning models on existence prediction tasks

(%)	Co-mention			Co-action		
	GRU	Attn	GRU+Attn	GRU	Attn	GRU+Attn
Precision	80.76	63.06	62.28	83.25	60.32	60.02
Recall	83.95	75.04	75.00	80.13	75.14	75.01
Macro F_1	82.32	68.53	68.05	81.66	66.92	66.68
Accuracy	78.82	75.31	75.86	79.55	70.91	73.60

Since our proposed models consistently outperform the baselines, we solely show the results of our models in Table 14. The training hyperparameters are identical with those of the numerical model; the threshold for the sigmoid layer is set to 0.45. All models achieve an accuracy above 0.7, ensuring users a robust set of results.

4.7.3. Additional experiment 3: Data augmentation

Furthermore, we augmented our dataset by randomly removing 20% of annotated news articles before detecting events. This approach enhanced the predictability when using co-mention history, while the results for co-action history remained strong, as shown in Table 15.

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Table 15 Model performance with augmented data

	MAE		**RMSE**	
	Co-mention	Co-action	Co-mention	Co-action
CAP (GRU+Attn)	0.8884	0.8001	1.0998	0.9865
CAP (Attn)	0.9107	0.8208	1.12	1.0105
CAP (GRU)	0.9924	0.9475	1.217	1.158
CAP (GRU+Attn w/ aug)	**0.8013**	0.8003	**0.9855**	**0.9855**
CAP (Attn w/ aug)	0.8245	0.8238	1.0096	1.0083
CAP (GRU w/ aug)	0.9207	0.9557	1.1311	1.1694

The enhanced predictability is attributed to lower competitor consistency in co-mention history. To calculate the consistency of competitors for the augmented sets, we utilize the Dice score between competitor sets. The Dice score between sets s_A and s_B is calculated as

$$\mathrm{Dice}(s_A, s_B) = 2 \times \frac{|s_A \cap s_B|}{|s_A| + |s_B|}. \tag{4.3}$$

As shown in Table 16, the Dice scores within the co-mention histories are lower (i.e., less similar) compared to those within the co-action histories. This indicates a higher degree of competitor variability in the co-mention setting, which, in turn, enhances predictability. The increased variability suggests that augmented data from news articles introduces more diverse competitor co-mention histories, thereby improving the efficiency of predictions using co-mention data. However, as co-action history is based on events instead of news articles, the augmentation of articles has a slightly smaller effect on predictability.

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Table 16 Dice scores between the original and augmented datasets

Co-action						**Average Dice: 0.864**
Dice	ORG	AUG #1	AUG #2	AUG #3	AUG #4	AUG #5
ORG	-	0.859	0.864	0.857	0.83	0.858
AUG #1	0.859	-	0.883	0.864	0.843	0.871
AUG #2	0.864	0.883	-	0.878	0.847	0.88
AUG #3	0.857	0.864	0.878	-	0.919	0.863
AUG #4	0.83	0.843	0.847	0.919	-	0.838
AUG #5	0.858	0.871	0.88	0.863	0.838	-

Co-mention						Average Dice: 0.904
	ORG	AUG #1	AUG #2	AUG #3	AUG #4	AUG #5
ORG	-	0.911	0.917	0.915	0.888	0.922
AUG #1	0.911	-	0.898	0.909	0.886	0.906
AUG #2	0.917	0.898	-	0.906	0.884	0.902
AUG #3	0.915	0.909	0.906	-	0.91	0.92
AUG #4	0.888	0.886	0.884	0.91	-	0.887
AUG #5	0.922	0.906	0.902	0.92	0.887	-

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5. Conclusion

We are among the first to propose a pipeline using a massive amount of news data to predict competitive actions. More specifically, in this study, we built an an auto-profiler to annotate and group news articles into events. We then identified competitors and formed competitive repertoires with two different approaches, either article based or action based. The competitors' action repertoires provided us information, assisting us to make predictions based on time series and the competitive landscape. The results can benefit firms in a given industry, investors, and third-party advisors.

When examining the key module, i.e., the CAP module, our experiments demonstrate that DL models significantly outperform traditional regression methods in predicting future actions. By incorporating more features in the initial layers, our models captured detailed data aspects, leading to enhanced performance. Additionally, an ensemble approach (combining GRUs and Attention) yields greater performance by leveraging the strengths of individual models for more robust and accurate predictions. We also found that utilizing co-action history provides greater insight into the competitive landscape, as opposed to using co-mention history.

On a higher level, our pipeline serves as a decision supporting tool and is beneficial for decision makers in two ways. For starters, it is flexible: the pipeline can be applied to other industries, a strategist can consider a different number of competitors (α), the

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window size, whether to predict existence or occurrence, using co-mention or co-action, etc. Moreover, it offers higher granularity than the explanatory models in previous literature. Instead of solely knowing the number of total competitive actions, it is knowing which actions its competitors tend to take that drives managers and executives to revise their strategies.

Future work could explore additional firm features as predictors, especially those used in predicting the volume and complexity of competitive actions. It is worth investigating whether these features can also contribute to the task of CAP. Network metrics can also be applied to identifying competitors, as measures such as clustering coefficients and centrality values could provide further insights into competitive relationships. Additionally, incorporating online travel agencies (OTAs), hotels and other players in the travel industry into future studies could extend the understanding of co-opetitive relations within a greater competitive landscape, offering new strategies and insights for industry players. While identifying action initiators and defenders is outside the scope of our study, modeling their relationships and roles would be an interesting future direction. Ultimately, this prediction model not only contributes to a deeper understanding of competitive dynamics but also supports downstream tasks such as performance prediction, making it a useful tool for various stakeholders in the airline industry.

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7. Appendix

7.1. List of airlines in our research (sorted by average revenue through 2011-2023)

Airline	Avg. Revenue in USD (M)	Airline	Avg. Revenue in USD (M)
Delta Airlines	39890.46	Ryanair	6476.73
United Airlines	37439.54	Hainan Airlines	5268.55
American Airlines	36992.54	easyJet	5106.20
Air France	25734.95	China Airlines	4571.18
Royal Dutch Airlines	25734.95	Thai Airways	4403.73
Lufthansa	25308.86	Asiana Airlines	4350.59
Emirates Airlines	25157.14	EVA Airways	4294.85
British Airways	20069.26	Scandinavian Airlines	3557.97
Iberia	20069.26	Skywest Airlines	3086.77
Southwest Airlines	19218.46	Malaysian Airlines	2940.80
China Southern Airlines	15131.00	Vietnam Airlines	2800.79
Air China	13705.26	Virgin Australia	2771.01
China Eastern Airlines	11444.97	Spirit Airlines	2747.08
Qatar Airways	11399.14	Air New Zealand	2729.21
Cathay Pacific Airways	11273.37	Aeromexico	2544.92
All Nippon Airways	10630.50	Finnair	2476.25
Singapore Airlines	10507.96	Indigo Airlines	2418.48
LATAM Airlines	9111.09	COPA Airlines	2332.14
Qantas Airways	8877.76	Frontier Airlines	2286.00
Korean Airlines	8805.36	Hawaiian Airlines	2232.59
Japan Airlines	7709.12	Norwegian Air Shuttle	2002.87
Alaska Air	6586.75	Turkish Airlines	1966.76
jetBlue Airways	6486.62		

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