A Case for Business Process-Specific Foundation Models

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Abstract

The inception of large language models has helped advance state-of-the-art performance on numerous natural language tasks. This has also opened the door for the development of foundation models for other domains and data modalities such as images, code, and music. In this paper, we argue that business process data representations have unique characteristics that warrant the development of a new class of foundation models to handle tasks like process mining, optimization, and decision making. These models should also tackle the unique challenges of applying AI to business processes which include data scarcity, multi-modal representations, domain specific terminology, and privacy concerns.

1 Introduction

Artificial intelligence, especially since the emergence of deep learning, has disrupted many areas of our lives from personal assistants like Alexa [Schneider, 2020] to autonomous driving [Bernhart and Winterhoff, 2016]. It has also been a disruptive force for businesses¹; deep learning is estimated to provide between \$3.5 trillion and \$5.8 trillion of annual value Chui et al. [2018] and can be the difference between companies' rise or demise.

In enterprise settings, business processes provide a structured framework for work. They define tasks, and identify their executors while capturing dependencies and providing logging and tracking capabilities. They also capture company policies and compliance with regulations. With many enterprises relying on the business process management paradigm to standardize their work, process management tools grew to a \$11.84 billion industry and is projected to grow to \$26 billion in 2028².

However, the existing landscape of work has been rapidly changing, requiring companies to move from their static business process practices to more agile and automated methods due to increased supply chain disruptions and skill shortages from the recent pandemic. Thus, companies are making significant investments to adopt AI-driven tools for tasks like process prediction, visualization, translation, etc. [McKendrick, 2021], evidenced by the \$1+ million investments made by companies and the projected \$3.2+ trillion business value produced by AI tech gar [2018]. Foundation models' recent success presents an opportunity to improve business process automation and management.

¹https://www.gartner.com/smarterwithgartner/the-disruptive-power-of-artificial-intelligence

²https://www.marketwatch.com/press-release/business-process-management-market-size-growth-with-top-leading-players-growth-key-factors-global-trends-industry-share-and-forecast-2022-2031-2022-08-18

³https://www.gartner.com/en/newsroom/press-releases/2021-09-29-gartner-finds-33-percent-of-technology-providers-plan-to-invest-1-million-or-more-in-ai-within-two-years



Figure 1: Example of a mortgage loan application process (Source: Chakraborti et al. [2020b])

Similar to natural language, images, or code snippets, business processes are yet another information representation paradigm. However, the unique and particular nature of process features and modalities can render existing foundation models inadequate to accurately understand and reason over them. Hence, developing successful foundation models for business process decision making requires research efforts to treat process data in a holistic manner instead of separate, independent modalities.

In this paper, we propose an approach to creating foundation models that factor in the complexity of process data. We also discuss some of the challenges of creating foundation models for business processes and the risks and opportunities of foundation models' emergent behavior. First, however, we provide an overview of business processes, their unique properties and the tasks⁴ that may be best suited for foundation models.

2 Background

2.1 Business Process Management

A business process is a collection of ordered tasks, followed by a business to produce a product or a service Weske [2012]. Figure 1 shows the example of a mortgage application process where every application must go through the same steps before a decision is made. This allows mortgage lenders to structure their process, improve consistency across loan officers and track the execution of the process for accountability, auditing and improving the provided service. A graphical notation, known as business process model and notation (BPMN) Grosskopf et al. [2009], is generally used to represent such processes, capturing the relationship between tasks (rectangular boxes with rounded edges) that must be completed by employee roles within an organization, events (circles) that can trigger processes or specific tasks within them, and decision points (diamonds) that allow paths within the process flow to merge or diverge. Swim lanes are usually defined to place specific tasks within the scope of an employee role or department. A trace is an execution of a process; each process can produce many distinct traces when executed depending on input events and other factors.

Business process management consists of many problems related to the modeling or design, execution and governance of processes. Process mining or discovery analyzes event data to identify and derive processes from raw, unstructured data Van Der Aalst [2012]. Ideally, process mining should produce a BPMN or similar representation for the discovered process. Process optimization or re-engineering looks to improve existing processes Arlbjørn and Haug [2010]. This requires making changes to the process representation while maintaining the properties that characterize a valid process. Conformance checking verifies that the "as-is" process (i.e., how the process is being executed in reality) does not deviate from the "to-be" process (i.e., how the process was theoretically designed to be executed) Dunzer et al. [2019]. Task automation through robotic process automation looks to create automation scripts that can programmatically execute tasks instead of humans Van der Aalst et al. [2018], whereas automation mining programmatically identifies the best tasks to automate Geyer-Klingeberg et al. [2018].

2.2 Foundation Models

Foundation models, coined in Bommasani et al. [2021], refer to deep neural network models trained on massive data and can be reused (with minimal modifications) for multiple downstream tasks.

⁴Since processes also call individual nodes within a process a task, we will use "downstream tasks" to refer to foundation model specific prediction tasks and "process tasks" to refer to tasks within a process.

A key characteristic of foundation models is "emergent" knowledge: the model is able to make predictions and perform downstream tasks that it has never seen before and wasn't trained on.

Large language models were the first examples of foundation models; trained on billions of English sentences from the internet, the models learned the structure of language and became capable of performing natural language understanding and generation tasks Devlin et al. [2019], Brown et al. [2020]. This has been followed by a wave of new foundation models catering to problems across different domains such as vision [Radford et al., 2021], programming code, clinical and biomedical applications [Alsentzer et al., 2019], among others.

After training foundation models (generally) in an unsupervised or self-supervised paradigm, one of two approaches can be taken to use the model for a specific task. Either fine-tune on a small set of labeled data or create a prompt from labeled data to input to the model along with the input you want a prediction for. Both approaches have their pros and cons and have spurred many new open research questions and subfields of AI (e.g., prompt engineering [Liu et al., 2021]).

3 A Business Process Foundation Model

3.1 Overview

The business process management literature is already rich with machine learning solutions to improve business processes (e.g. Nguyen et al. [2022]). In recent years, there has been increased adoption of AI techniques (including natural language processing) in business processes for problems including predicting the next task or outcome of a process Teinemaa et al. [2019], Evermann et al. [2016], the remaining execution time of the process Tax et al. [2017], Navarin et al. [2017], decision support Agarwal et al. [2022], resource allocations Żbikowski et al. [2021], detecting drifts in process execution, and anomalous executions Huo et al. [2021]. Declarative AI planning Chakraborti et al. [2020a] and reinforcement learning Silvander [2019] have been used for process optimization. Natural language understanding has been used to declaratively extract process models Aa et al. [2019] and to provide conversational interfaces López et al. [2019], Rizk et al. [2020].

What all these problems have in common is a fundamental understanding of what a process is, its constituting components, its properties and its goals. However, the current narrow view of the literature when tackling these problems would lead to narrow solutions that may not realize the full potential of AI, especially when considering what foundation models could do. If we are able to encode this information in a foundation model, then we would be able to leverage this model to perform some of the tasks mentioned above.

Foundation models for language learn the building blocks of language. There is a finite number of letters that words are made up of; not all letter sequences produce valid words. Sentences are composed of word sequences that must abide by the syntactic structures imposed by language. Words play specific syntactic and semantic roles within sentences and can have various semantic meanings based on context. Sentences also convey a semantic meaning that must be understood by the entity (person or otherwise) decoding the sentence. Similarly, foundation models for images learn that pixels with coordinates and values (in gray-scale or RGB or others) are combined to form lines that create shapes which have colors. An image has a foreground and a background; objects within an image have various spacial relationships with each other.

For business processes, foundation models need to learn about process artifacts, notation, and properties. Furthermore, intra- and inter-process features have been shown to have an effect on the prediction Senderovich et al. [2017]. Once a deep learning network internalizes all these concepts, then we can start performing more complex downstream tasks that rely on this foundational understanding like optimizing processes or discovering them from unstructured data and events.

3.2 Data Types in Business Processes

The data describing business processes and generated from their execution consists of many different types of data. Whether we consider business process data to be a new modality in machine learning Chakraborti et al. [2020b] or treat it as a multi-modal problem, we first need to understand what types of data exist before we can effectively train foundation models.

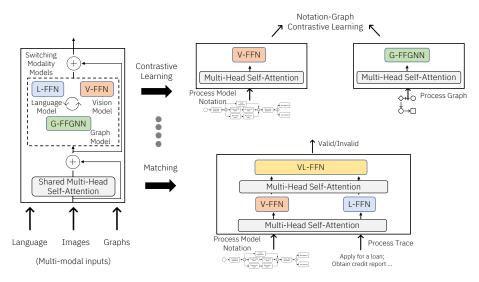


Figure 2: Using Mixture of Modality Experts (MoME) Transformer to pre-train a Business Process Foundation Model on different tasks

The first type of data embodied in a business process is a graph which represents the control flow of a process where tasks and decision points are connected to form a directed graph with cycles, branches, root nodes and end nodes White [2004]. Once a process is executed, a sequence of events is generated, referred to as a process trace. One process may have many different traces representing the various traversals of the graph and different decisions at decision points.

Processes also have metadata associated with the process and with the events within a process which are generally represented by a multi-dimensional set of attributes that can be binary, categorical or continuous. For example, each task in the process is typically associated with a human worker (e.g., loan officer, claims processor) from the enterprise organization, who are geographically distributed, have different working timezone, vacation, and holiday schedules. These human workers cannot work on two process cases at once, which in turn creates an implicit limit on the number of associated concurrent tasks across process instances. Events and tasks within a process can also have unstructured documents associated with them (e.g., images, text, video, audio). Interactions between participants (including social networks) in a process can be represented by graphs and times series data.

Considering only a subset of data would provide an incomplete view of the business process and may lead to sub-optimal predictions by machine learning models. Thus, it is important to identify effective approaches to handle these types of complex applications and interactions with diverse data types.

3.3 Downstream Tasks

We distinguish between two types of downstream tasks for foundation models: domain agnostic vs. domain specific. Domain agnostic downstream tasks can be process mining, process optimization, trace prediction, etc. Domain specific downstream tasks can be process task prediction, decision recommendation at a decision point in a process, automation of process tasks, etc. Furthermore, some of these downstream tasks can be time sensitive vs. not. For example, identifying a process from unstructured data can be performed offline. However, a decision making step during process execution is more time sensitive; the foundation model needs to make a decision within seconds or minutes (possibly) as opposed to hours or days. Depending on the type of downstream tasks, we may need different versions of foundation models (e.g., computational heavy vs. light-weight).

3.4 Model Architecture

Past work on pre-training foundation models in multi-modal settings have focused on Vision-Language tasks. They learn cross-modal representations to align information using approaches like contrastive learning, matching, masked modeling, etc [Radford et al., 2021, Kim et al., 2021,

Yu et al., 2022]. These efforts primarily use one of two architectures. The first is a *dual-encoder* architecture to encode different data modalities separately, and then use cosine-similarity of the feature vectors for modality interaction. This shallow interaction between the different modalities has been shown to perform poorly on several tasks [Jia et al., 2021]. The second is a *fusion-encoder* architecture with cross-modal attention, to jointly encode all possible data pairs to compute similarity scores for tasks. This results in a quadratic (for two modalities) time complexity and much slower inference speed than dual-encoder models whose time complexity is linear.

We envision leveraging a recent approach, called Mixture-of-Modality-Experts (MoME) [Wang et al., 2021, 2022], that uses a pool of modality models to replace the feed-forward network in a standard transformer architecture. It switches between different modality models to capture modality-specific information, and then uses shared self-attention across modalities to align information. Figure 2 describes our vision for implementing MoME for business process tasks, where we define expert feed-forward network (FFN) and feed-forward graph neural network (FFGNN) models for different modalities (language, vision, graph) and their combinations.

Depending on the modality of the input vectors, the transformer selects the appropriate mixture of expert models to process the input. For instance, if the input consists of vectors representing process traces and process model notations, the transformer would pick the language and vision models to encode the inputs and a vision-language model to capture more modality interactions. Traditional pre-training tasks like contrastive learning, masking, matching, etc, can be performed to capture cross-modal information in the business process context, and we show an example of two pre-training tasks in Figure 2.

4 Challenges

4.1 Data Scarcity and Privacy Concerns

A majority of foundation model training efforts consider tasks involving the generation of natural language (e.g., OpenAI GPT-3, Google T5), images (e.g., the recent DALL·E 2 model) or code syntax (e.g., GitHub Copilot, Amazon CodeWhisperer). An inherent advantage of these tasks, is the prevalence of a variety of relevant and labeled/unlabeled training data that have been collected and open-sourced by the larger research community.

However, for business processes, there is a lack of sufficient labeled open-source real-world data to train foundation models. A big reason for this, is the inherent proprietary nature of business processes, resulting in most corporations being unwilling to share their data and models. While there have been some efforts towards democratizing business process data, such as the Business Process Intelligence (BPI) Challenges⁵, they have also stated the growing difficulties in obtaining real-world data from corporations, citing privacy concerns.

Therefore, enabling foundation models for business processes would require addressing the critical challenge of data availability. This could entail solutions involving privacy-preserving training such as federated learning approaches, wherein models can be trained on data across multiple business units and corporations without involving any data sharing. Other possible solutions could involve data generation and augmentation techniques to leverage patterns from the literature (e.g., insertion of new tasks in the process, optionalization of tasks that were previously required in the process, and resequentialization of tasks Maaradji et al. [2017]) or ones existing in the data to create realistic new process data. Generative models (e.g., GANs) could be used to create new data instances hallucinated from existing processes. However, such approaches would also require crowd-sourced data validation (by subject matter experts) and labeling efforts to ensure training data quality.

4.2 Breadth of Tasks

As with other domains, business process mining, monitoring, and automation can comprise of a multitude of possible tasks. These could be (1) process predictions – such as predicting a future process sequence given a partial trace, process completion time, process failures, etc., (2) process synthesis – including synthesising new process models from specifications or natural language input,

⁵https://www.tf-pm.org/newsletter/newsletter-stream-2-05-2020/bpi-challenges-10-years-of-real-life-datasets

process visualizations, etc., (3) explainability and summarization – wherein models are expected to explain various business process decisions and predictions, as well as provide accurate summaries of process traces, among other tasks.

These tasks involve different data modalities and input/output structures. Some of these tasks operate using text, some with images, and others with graphs. Hence, training a singular foundation model across these different tasks is a significant challenge. Determining the appropriate model parameters in this situation would require techniques like meta-learning [Finn et al., 2017] to ensure minimal additional training to perform well on different downstream tasks.

There have been several recent research efforts to incorporate multi-modality in foundation models. For example, Zeng et al. [2022] propose a prompt-driven approach to combine language, vision and audio models in a symbiotic manner to exchange information with each other and capture multi-modal knowledge. Similarly, Wang et al. [2022] propose a multi-modal foundation model BEIT-3 for vision and language tasks, that uses a multiway transformers network to align various modalities. However, these models do not work for many business process automation tasks, thereby requiring a new foundation model initiative.

4.3 Domain Specific Language

Tasks based on natural language have well-defined language constructs and semantic meaning for models to reason on. However, business processes often have acronyms and technical phrases which are not common knowledge, but are critical for the model to understand. Additionally, process models often adhere to different standards and graphical notations such as the Business Process Model and Notation (BPMN), Decision Model and Notation (DMN), Case Management Model and Notation (CMMN), etc. [White, 2004, Wiemuth et al., 2017].

Hence, it is a critical challenge to develop a domain specific language (DSL) to enable foundation models to reason over such business process specific terminology. In addition, such a DSL would also enable users to enforce business policies and ensure the validity of the model outputs using techniques such as constrained semantic decoding [Poesia et al., 2022]. However, the number of business domains and terminology is ever-increasing and nearly impossible to fully capture. This would result in situations where the model has limited knowledge or information, reflecting zero-shot or few-shot settings, that would require approaches like prompt-based fine-tuning of the model.

4.4 Prompt Engineering for Business Processes

Many real-world tasks may have very little, or no data available to fine-tune foundation models. However, the use of prompts and in-context examples have been shown to enable language models to perform significantly well in zero-shot and few-shot settings [Radford et al., 2019, Brown et al., 2020, Sanh et al., 2021]. The popularity of language tasks has even resulted in a public repository [Bach et al., 2022] of natural language prompts.

While the use of prompts has demonstrably improved performance, foundation models have also been shown to be extremely sensitive to prompt engineering. For instance, Zhao et al. [2021] and Min et al. [2022] have shown that small changes to the prompt such as changing the prompt structure, reordering, and even the number of examples, can result in a significant drop in model performance. They also demonstrate how model biases arising from the pre-training data, can impact its performance when fine-tuned for downstream tasks.

This presents several challenges for business process models. Firstly, while the structure of prompts may often be straightforward for language tasks (e.g., questions for question-answering), this is not the case for many business process tasks. For instance, tasks involving the translation of natural language specifications to process models or summarizing process models using text, would require careful prompt engineering. Prompts in the business process domain can involve images or even graph structures, and identifying the most relevant examples or prompts also presents a challenge. Moreover, ensuring the robustness of the model to biases during the pre-training process is critical.

4.5 Human-in-the-loop Feedback and Model Robustness

Many process automation tasks involve critical decision-making steps. The sensitive and regulated nature of business domains often results in the requirement of human feedback to be present as part

of the decision making pipeline. This feedback could involve the enforcement of corporate policies, ensuring the validity of model outputs, changes to intermediate decisions of the process pipeline, among others. Hence, process models would require an optimized approach to incorporate such human-in-the-loop feedback. Since fine-tuning large foundation models is an expensive process, it may not always be possible to continually update the model parameters with user feedback, thereby requiring approaches to incorporate the feedback within subsequent input prompts.

Additionally, the influence of malicious actors and data biases on model decisions can have a significant and costly impact on businesses. For instance, adversarial prompts and feedback could be used to bias the model to output incorrect or inappropriate decisions, or even obtain any confidential information used to train or fine-tune the model [Bommasani et al., 2021, Carlini et al., 2021]. Hence, approaches to improve model robustness are critical for business process tasks. For instance, coupling constrained decoding with model outputs, where businesses can explicitly specify guardrails or policies [Rizk et al., 2022], and careful consideration of data biases, distribution shifts, and information leakage during the pre-training process are important.

5 Risks, Opportunities, and Next Steps

The emergent behavior of foundation models has been a point of intrigue and concern in various fields like healthcare Wiggins and Tejani [2022] and education Blodgett and Madaio [2021]. For, business processes, things are no different. On the one hand, as foundation models become capable of generating, modifying and executing parts of a process, concerns around violating industry standards or company policies, auditability and interpretability must be addressed to ensure wide-spread adoption. On the other hand, using generative models to produce new business processes can unlock tremendous optimizations and new ways to do work that can help business achieve profitability without sacrificing sustainability and environmental impact. Also, foundation models can help make data driven decision making a reality for business processes.

In summary, we believe that foundation models for business processes have tremendous potential to advance the field of process management and integrate AI into their practices. Both AI and BPM communities need to join forces to create the proper infrastructure to train and use such foundation models. Next steps for the community include identifying existing data sources and curating specialized datasets for training and fine-tuning. Safeguards should also be put in place to ensure that foundation models' emergent behavior does not have negative side-effects that may hinder its adoption in industry.

References

Gartner says global artificial intelligence business value to reach \$1.2 trillion in 2018. 2018.

Han van der Aa, Claudio Di Ciccio, Henrik Leopold, and Hajo A Reijers. Extracting declarative process models from natural language. In *Int. Conf. Advanced Information Systems Engineering*. Springer, 2019.

Prerna Agarwal, Buyu Gao, Siyu Huo, Prabhat Reddy, Sampath Dechu, Yazan Obeidi, Vinod Muthusamy, Vatche Isahagian, and Sebastian Carbajales. A process-aware decision support system for business processes. In *Proc. ACM SIGKDD Conf. Knowledge Discovery and Data Mining*, pages 2673–2681, 2022.

Emily Alsentzer, John R Murphy, Willie Boag, Wei-Hung Weng, Di Jin, Tristan Naumann, and Matthew McDermott. Publicly available clinical bert embeddings. *arXiv preprint arXiv:1904.03323*, 2019.

Jan Stentoft Arlbjørn and Anders Haug. Business process optimization. Academica, 2010.

Stephen H Bach et al. Promptsource: An integrated development environment and repository for natural language prompts. *arXiv* preprint *arXiv*:2202.01279, 2022.

Wolfgang Bernhart and Marc Winterhoff. Autonomous driving: Disruptive innovation that promises to change the automotive industry as we know it. In *Energy Consumption and Autonomous Driving*. Springer, 2016.

Su Lin Blodgett and Michael Madaio. Risks of ai foundation models in education. *arXiv preprint* arXiv:2110.10024, 2021.

Rishi Bommasani et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.

- Tom Brown et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- Nicholas Carlini et al. Extracting training data from large language models. In 30th USENIX Security Symposium (USENIX Security 21), pages 2633–2650, 2021.
- Tathagata Chakraborti, Shubham Agarwal, Yasaman Khazaeni, Yara Rizk, and Vatche Isahagian. D3ba: a tool for optimizing business processes using non-deterministic planning. In *Int. Conf. Business Process Management*, pages 181–193. Springer, 2020a.
- Tathagata Chakraborti, Vatche Isahagian, Rania Khalaf, Yasaman Khazaeni, Vinod Muthusamy, Yara Rizk, and Merve Unuvar. From robotic process automation to intelligent process automation. In *Int. Conf. Business Process Management*, 2020b.
- Michael Chui, Nicolaus Henke, and Mehdi Miremadi. Most of ai's business uses will be in two areas. *Harvard Business Review*, 20, 2018.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *Proc. Conf. NAACL: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, 2019.
- Sebastian Dunzer, Matthias Stierle, Martin Matzner, and Stephan Baier. Conformance checking: a state-of-the-art literature review. In *Proc. 11th Int. Conf. subject-oriented business process management*, pages 1–10, 2019.
- Joerg Evermann, Jana-Rebecca Rehse, and Peter Fettke. A deep learning approach for predicting process behaviour at runtime. In *Int. Conf. Business Process Management*, pages 327–338. Springer, 2016.
- Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Int. Conf. machine learning*, pages 1126–1135. PMLR, 2017.
- Jerome Geyer-Klingeberg, Janina Nakladal, Fabian Baldauf, and Fabian Veit. Process mining and robotic process automation: A perfect match. In *BPM* (*Dissertation/Demos/Industry*), pages 124–131, 2018.
- Alexander Grosskopf, Gero Decker, and Mathias Weske. *The process: business process modeling using BPMN*. Meghan Kiffer Press, 2009.
- Siyu Huo, Hagen Völzer, Prabhat Reddy, Prerna Agarwal, Vatche Isahagian, and Vinod Muthusamy. Graph autoencoders for business process anomaly detection. In *Int. Conf. Business Process Management*, 2021.
- Chao Jia, Yinfei Yang, Ye Xia, Yi-Ting Chen, Zarana Parekh, Hieu Pham, Quoc Le, Yun-Hsuan Sung, Zhen Li, and Tom Duerig. Scaling up visual and vision-language representation learning with noisy text supervision. In *ICML*, pages 4904–4916. PMLR, 2021.
- Wonjae Kim, Bokyung Son, and Ildoo Kim. Vilt: Vision-and-language transformer without convolution or region supervision. In ICML, pages 5583–5594. PMLR, 2021.
- Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *arXiv* preprint *arXiv*:2107.13586, 2021.
- Anselmo López, Josep Sànchez-Ferreres, Josep Carmona, and Lluís Padró. From process models to chatbots. In *Int. Conf. Advanced Information Systems Engineering*, pages 383–398. Springer, 2019.
- Abderrahmane Maaradji, Marlon Dumas, Marcello La Rosa, and Alireza Ostovar. Detecting sudden and gradual drifts in business processes from execution traces. *IEEE Transactions on Knowledge and Data Engineering*, 29(10):2140–2154, 2017.
- Joe McKendrick. Ai adoption skyrocketed over the last 18 months. Harvard Business Review, 2021.
- Sewon Min, Xinxi Lyu, Ari Holtzman, Mikel Artetxe, Mike Lewis, Hannaneh Hajishirzi, and Luke Zettlemoyer. Rethinking the role of demonstrations: What makes in-context learning work? *arXiv preprint arXiv:*2202.12837, 2022.
- Nicolo Navarin, Beatrice Vincenzi, Mirko Polato, and Alessandro Sperduti. Lstm networks for data-aware remaining time prediction of business process instances. In *IEEE Symposium Series on Computational Intelligence (SSCI)*, 2017.
- Phuong Nguyen, Vatche Isahagian, Vinod Muthusamy, and Aleksander Slominski. Summarizing process traces for analysis tasks: An intuitive and user-controlled approach. In *Int. Joint Conf. Artificial Intelligence*, 2022.

- Gabriel Poesia, Oleksandr Polozov, Vu Le, Ashish Tiwari, Gustavo Soares, Christopher Meek, and Sumit Gulwani. Synchromesh: Reliable code generation from pre-trained language models. *arXiv preprint arXiv:2201.11227*, 2022.
- Alec Radford et al. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9, 2019.
- Alec Radford et al. Learning transferable visual models from natural language supervision. In *ICML*, pages 8748–8763. PMLR, 2021.
- Yara Rizk, Vatche Isahagian, Scott Boag, Yasaman Khazaeni, Merve Unuvar, Vinod Muthusamy, and Rania Khalaf. A conversational digital assistant for intelligent process automation. In *BPM*, 2020.
- Yara Rizk, Praveen Venkateswaran, Vatche Isahagian, Vinod Muthusamy, and Kartik Talamadupula. Can you teach robotic process automation bots new tricks? In *Int. Conf. Business Process Management*, 2022.
- Victor Sanh et al. Multitask prompted training enables zero-shot task generalization. arXiv preprint arXiv:2110.08207, 2021.
- Florian Schneider. How users reciprocate to alexa. In *Int. Conf. Human-Computer Interaction*, pages 376–383. Springer, 2020.
- Arik Senderovich, Chiara Di Francescomarino, Chiara Ghidini, Kerwin Jorbina, and Fabrizio Maria Maggi. Intra and inter-case features in predictive process monitoring: A tale of two dimensions. In *BPM*, 2017.
- Johan Silvander. Business process optimization with reinforcement learning. In *Int. Symposium on Business Modeling and Software Design*, pages 203–212. Springer, 2019.
- Niek Tax, Ilya Verenich, Marcello La Rosa, and Marlon Dumas. Predictive business process monitoring with lstm neural networks. In *Int. Conf. Advanced Information Systems Engineering*. Springer, 2017.
- Irene Teinemaa, Marlon Dumas, Marcello La Rosa, and Fabrizio Maria Maggi. Outcome-oriented predictive process monitoring: review and benchmark. *ACM Trans. Knowledge Discovery from Data*, 13(2):1–57, 2019.
- Wil Van Der Aalst. Process mining: Overview and opportunities. *ACM Trans. Management Information Systems*, 3(2):1–17, 2012.
- Wil MP Van der Aalst, Martin Bichler, and Armin Heinzl. Robotic process automation, 2018.
- Wenhui Wang, Hangbo Bao, Li Dong, and Furu Wei. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. *arXiv* preprint arXiv:2111.02358, 2021.
- Wenhui Wang et al. Image as a foreign language: Beit pretraining for all vision and vision-language tasks. *arXiv* preprint arXiv:2208.10442, 2022.
- Mathias Weske. Business process management methodology. In Business Process Management, pages 373–388. Springer, 2012.
- Stephen A White. Introduction to bpmn. Ibm Cooperation, 2(0):0, 2004.
- Markus Wiemuth et al. Application fields for the new object management group (omg) standards case management model and notation (cmmn) and decision management notation (dmn) in the perioperative field. *Int. J. computer assisted radiology and surgery*, 12(8):1439–1449, 2017.
- Walter F Wiggins and Ali S Tejani. On the opportunities and risks of foundation models for natural language processing in radiology. *Radiology: Artificial Intelligence*, 4(4):e220119, 2022.
- Jiahui Yu, Zirui Wang, Vijay Vasudevan, Legg Yeung, Mojtaba Seyedhosseini, and Yonghui Wu. Coca: Contrastive captioners are image-text foundation models. *arXiv preprint arXiv:2205.01917*, 2022.
- Kamil Żbikowski, Michał Ostapowicz, and Piotr Gawrysiak. Deep reinforcement learning for resource allocation in business processes. arXiv preprint arXiv:2104.00541, 2021.
- Andy Zeng et al. Socratic models: Composing zero-shot multimodal reasoning with language. *arXiv* preprint arXiv:2204.00598, 2022.
- Zihao Zhao, Eric Wallace, Shi Feng, Dan Klein, and Sameer Singh. Calibrate before use: Improving few-shot performance of language models. In *ICML*, pages 12697–12706. PMLR, 2021.