



NATURAL LANGUAGE PROCESSING FOR BUSINESS PROCESS ANALYSIS

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STRUCTURE OF THIS TUTORIAL

- 1 Brief Introduction to NLP
- 2 Using NLP for Business Process Analysis
- 3 Hands-on Session
- 4 Discussion



PART 1: BRIEF INTRODUCTION TO NLP

NATURAL LANGUAGE PROCESSING

- Natural language processing (NLP) is concerned with the communication between computers and humans in natural language. In essence, NLP is all about making computers understand and generate human language.
- NLP is often subdivided into three main areas:
 1. Speech recognition—the translation of spoken language into text.
 2. Natural language understanding—a computer's ability to understand language.
 3. Natural language generation—the generation of natural language by a computer.



WHY IS NLP CHALLENGING?

Simple string comparisons do not get us very far.

1. Contextual words and phrases and homonym

I ran to the store because we ran out of milk.

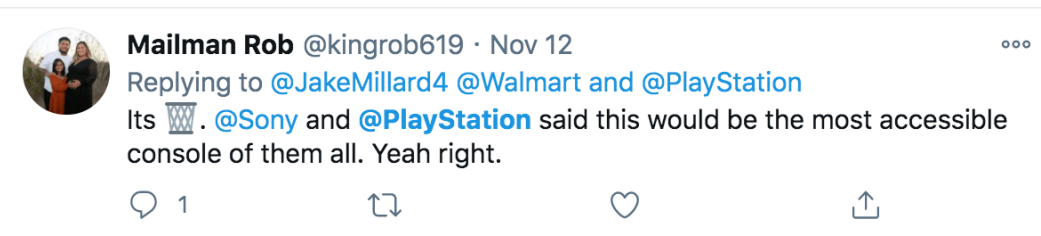
Can I run something past you real quick?

The house is looking really run down.

2. Synonyms

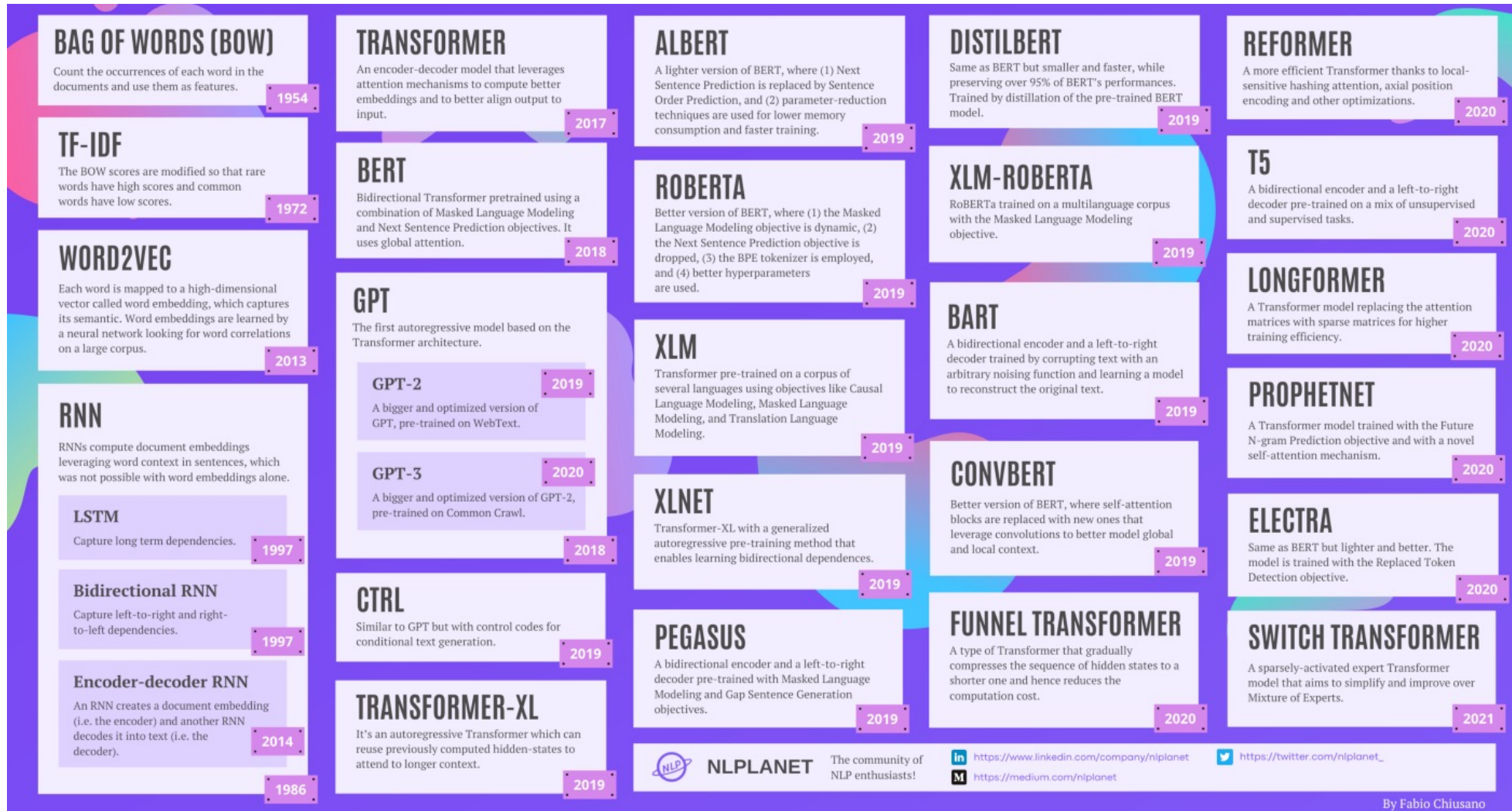
small, little, tiny, minute

3. Irony and sarcasm



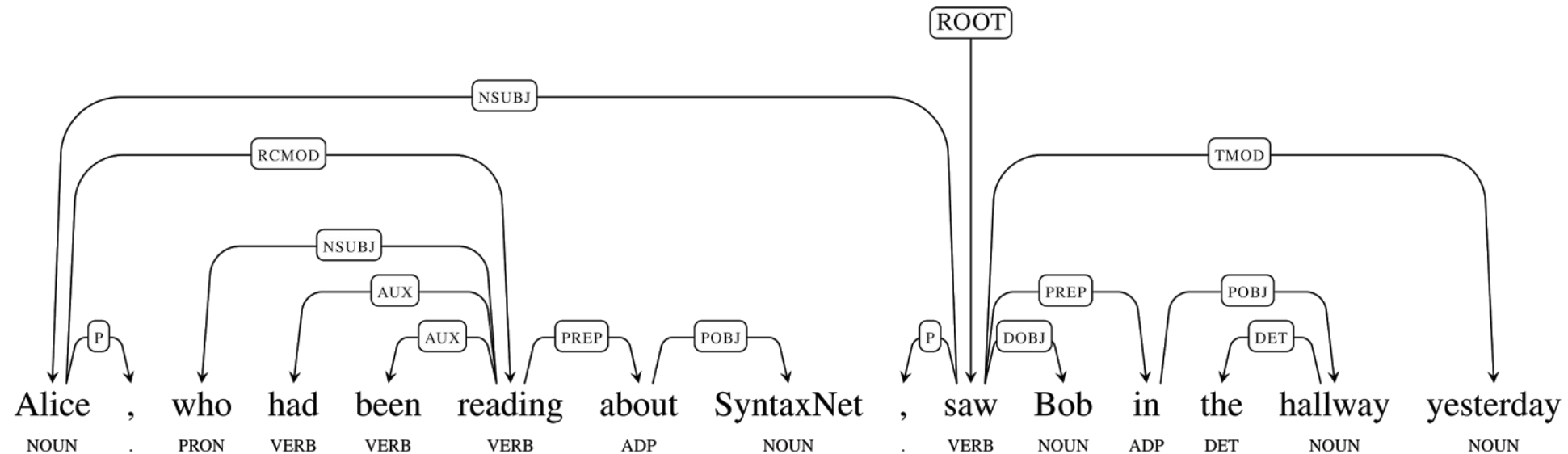
4. Errors, ambiguity, slang, etc.

DEVELOPMENTS IN NLP

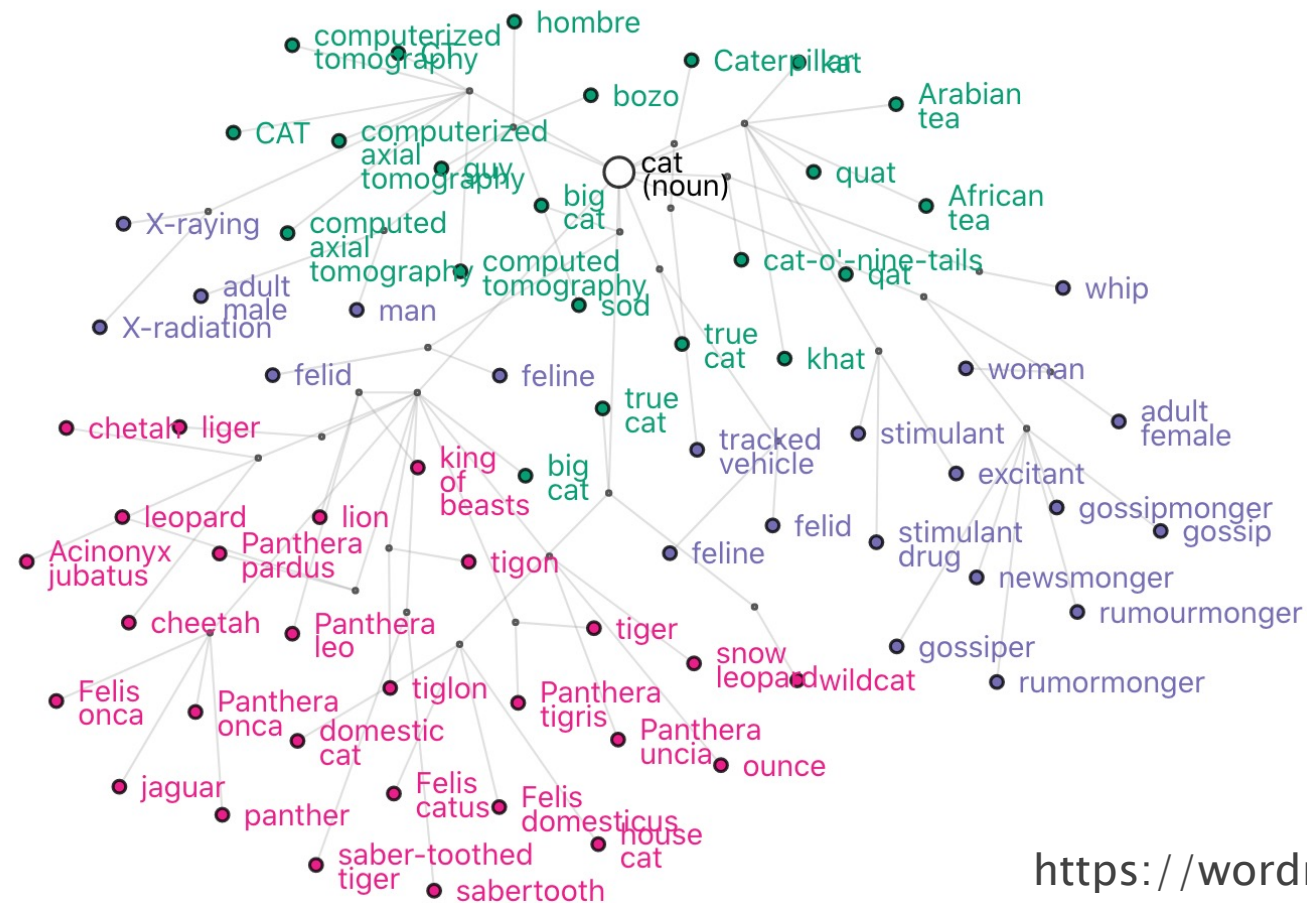


TOOLS WE USED IN BPM RESEARCH IN THE PAST

- <https://nlp.stanford.edu/software/lex-parser.html>

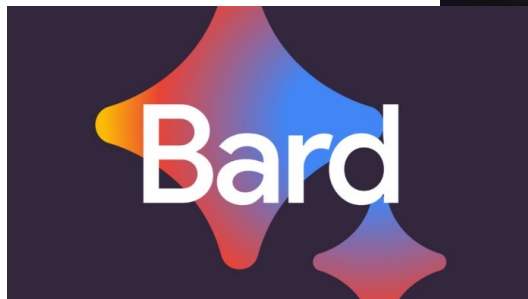


TOOLS WE USED IN BPM RESEARCH IN THE PAST



<https://wordnet.princeton.edu/>

TODAY: IT IS ALL ABOUT LARGE LANGUAGE MODELS (LLMs)



BRIEF INTRODUCTION TO LANGUAGE MODELING

Early one morning the sun was shining

I was laying in bed

wondering if she had changed at all

if her hair was still red

Bob Dylan, *Tangled up in Blue*

BRIEF INTRODUCTION TO LANGUAGE MODELING

Early → one → morning → the → sun → was → shining → I → was → laying → in → bed

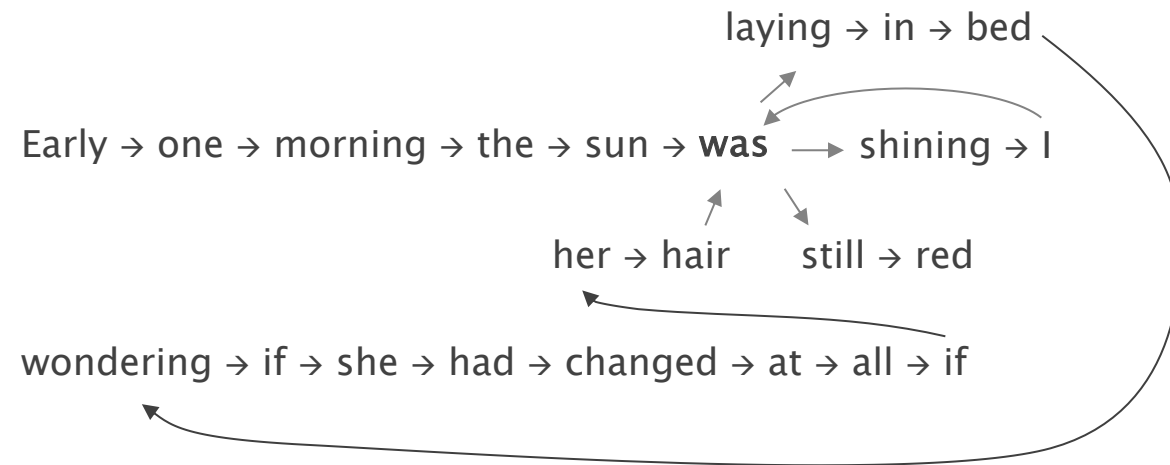
↖ wondering → if → she → had → changed → at → all → if → her → hair → was → still → red

BRIEF INTRODUCTION TO LANGUAGE MODELING

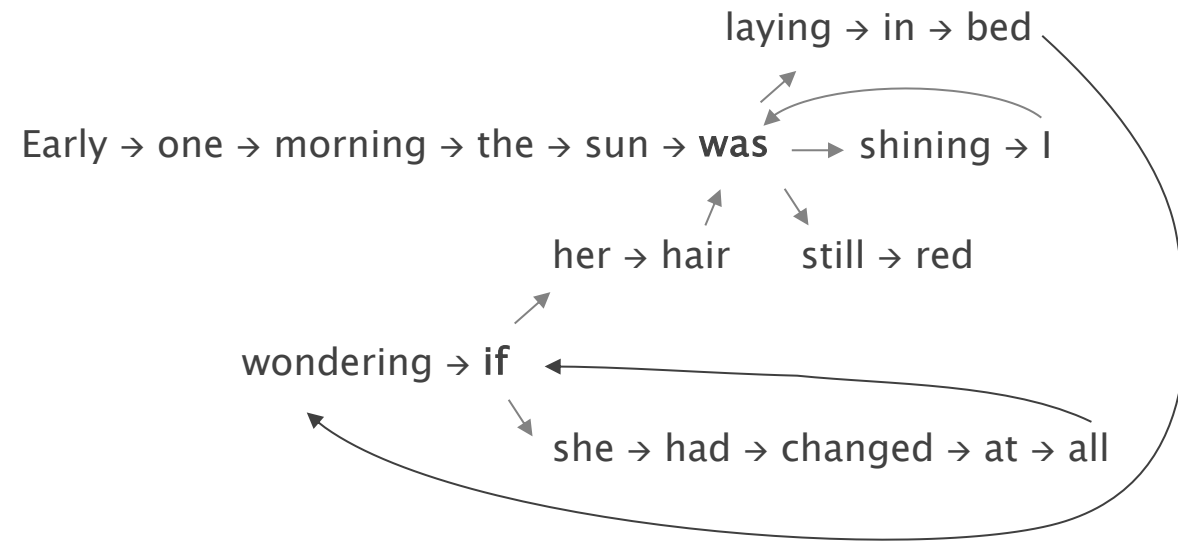
Early → one → morning → the → sun → **was** → shining → I → **was** → laying → in → bed

↖ wondering → **if** → she → had → changed → at → all → **if** → her → hair → **was** → still → red

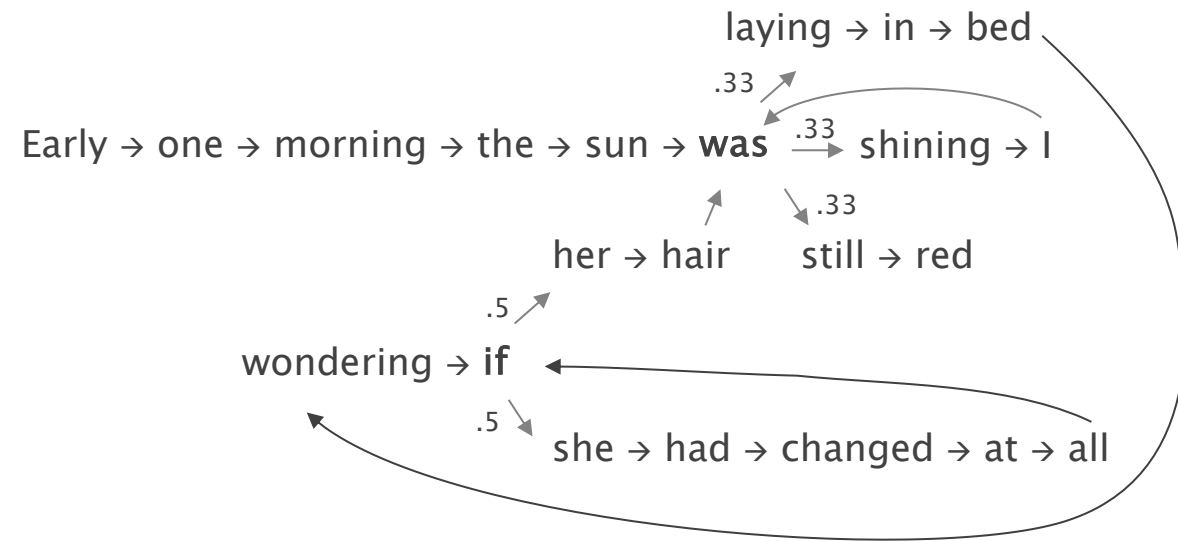
BRIEF INTRODUCTION TO LANGUAGE MODELING



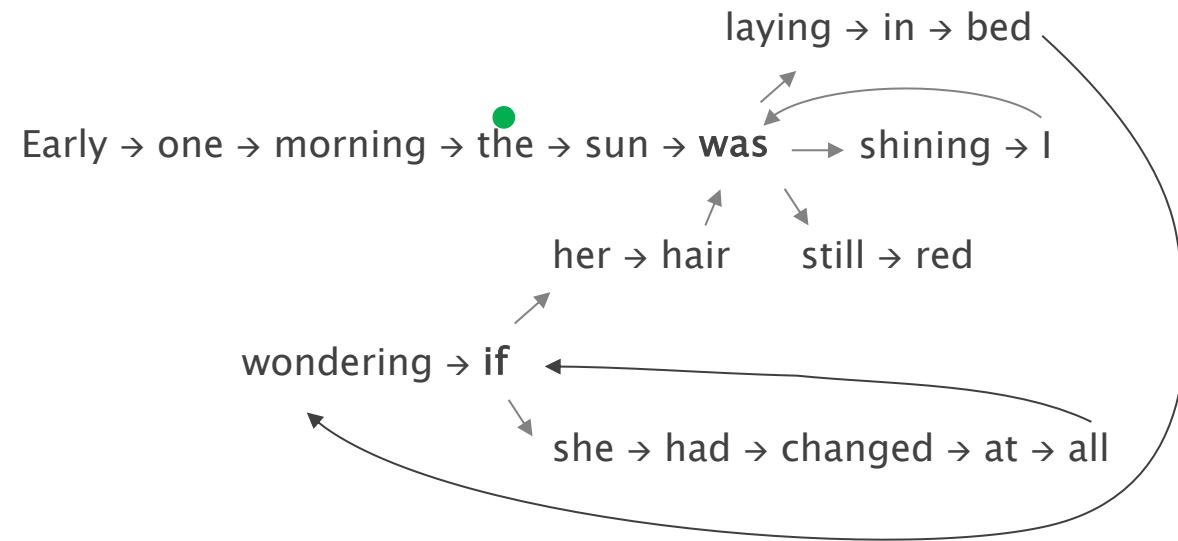
BRIEF INTRODUCTION TO LANGUAGE MODELING



BRIEF INTRODUCTION TO LANGUAGE MODELING

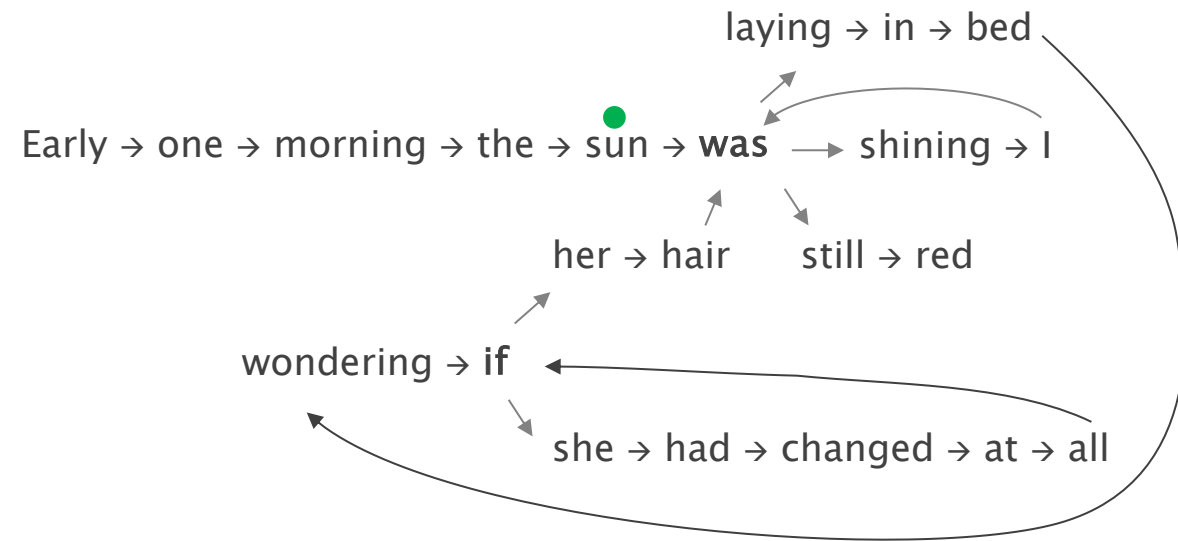


BRIEF INTRODUCTION TO LANGUAGE MODELING



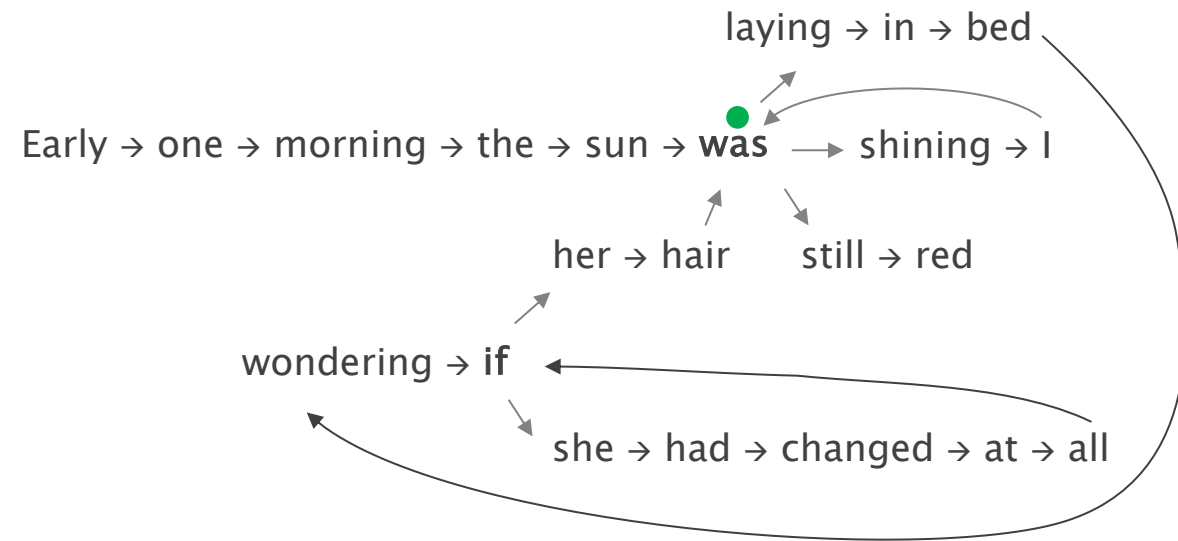
the

BRIEF INTRODUCTION TO LANGUAGE MODELING



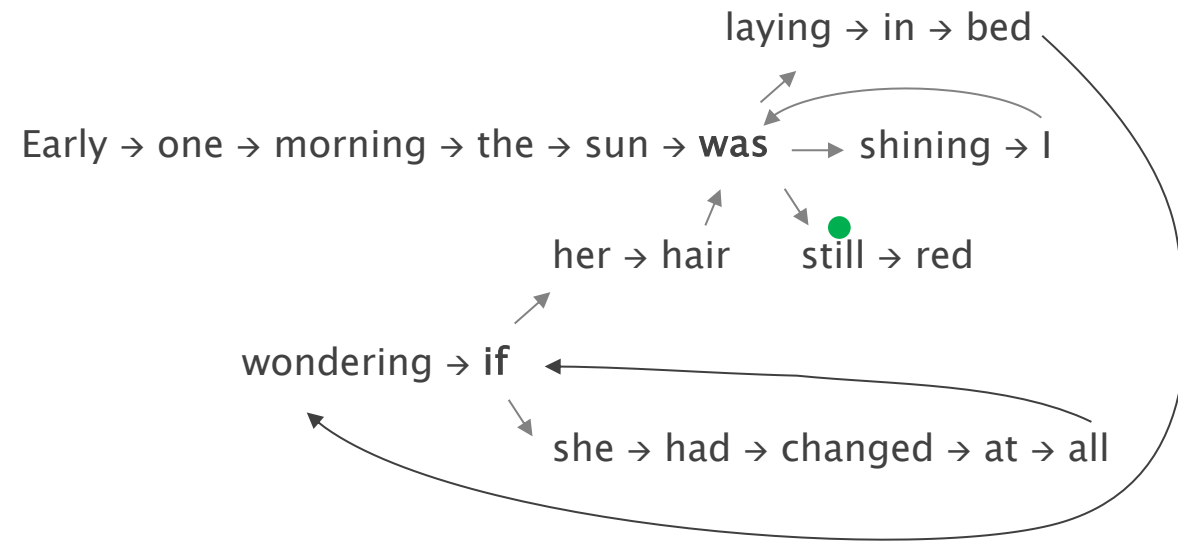
the sun

BRIEF INTRODUCTION TO LANGUAGE MODELING



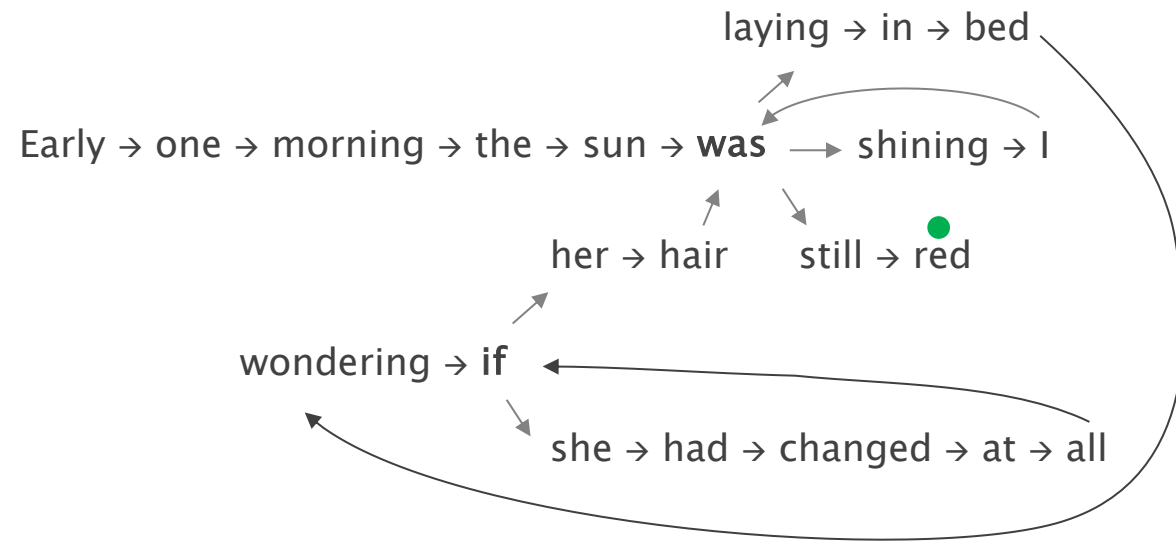
the sun was

BRIEF INTRODUCTION TO LANGUAGE MODELING



the sun was still

BRIEF INTRODUCTION TO LANGUAGE MODELING



the sun was still red



OUR LANGUAGE MODEL HAS SEVERAL ISSUES

Generalization to unseen data

Early **one** morning the sun was shining

I was laying in bed

wondering if she had changed at all

if her hair was still red

Early **yesterday**

→ ... ?

Early **Monday**

→ ... ?

Long-distance dependencies

Early one morning the sun was shining

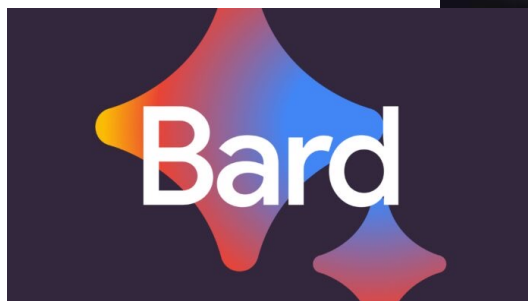
I was laying in **bed**

wondering if she had changed at all


if her **hair** was still **red**




LARGE LANGUAGE MODELS (LLMs)




MRKL SYSTEM: MOTIVATION




"Which US cities have more than 20M citizens?"



New York, Los Angeles, Chicago, Houston, Philadelphia, Phoenix, San Antonio, San Diego, Dallas, San Jose, Austin, Jacksonville, Indianapolis, Columbus




"How many teeth does a person have?"




32


"How many teeth does a math teacher have?"




47




"What's the date today?"
(asked on Dec 7, 2021)



Today is the 21st of December




"What is 10+11"



21

"What is 1982+39"



1981

MRKL SYSTEM: IDEA



A MRKL system consists of

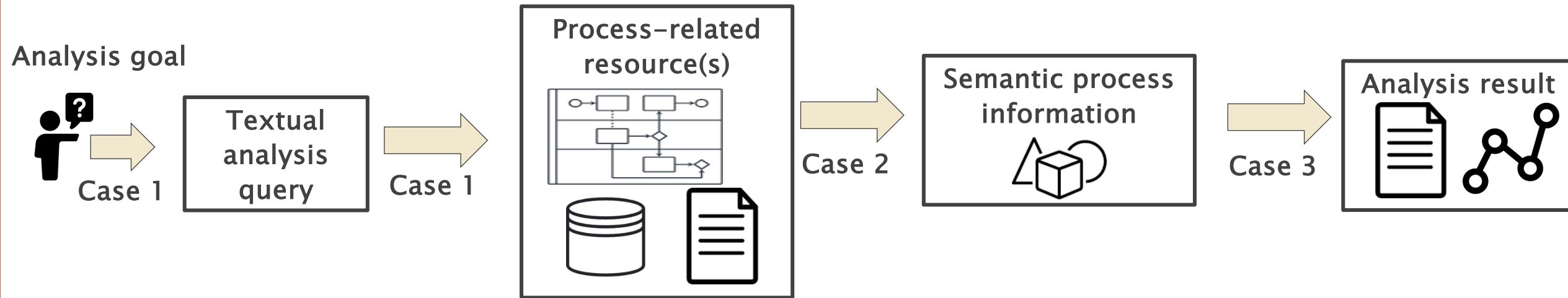
- an extendable set of modules (“experts”)
- and a router that routes every incoming natural language input to a module that can best respond to the input.

These modules can be:

- Neural, including the general-purpose huge language model as well as other smaller, specialized LMs.
- Symbolic, for example a math calculator, a currency converter or an API call to a database.

PART 2: USING NLP FOR BUSINESS PROCESS ANALYSIS

NLP FOR BUSINESS PROCESS ANALYSIS: OVERVIEW



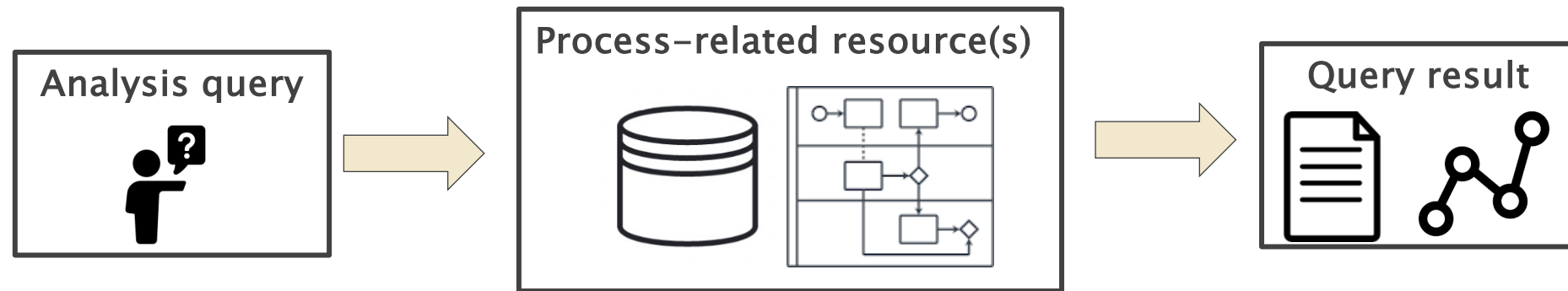
There are three main manners through which NLP is used in business process analysis:

1. **As an interface** for easier process analysis (textual queries, chatbots, etc.)
2. **To extract process information from text** in process-related resources (explicitly structured, such as process models and event logs, as well as process-related texts, such as textual descriptions, work instructions, or compliance documents)
3. **Semantics-aware process analysis** (techniques that use textual process information)

NLP-related process analysis pipelines may use one, two, or all three of these cases

CASE 1: NLP AS AN INTERFACE FOR PROCESS ANALYSIS

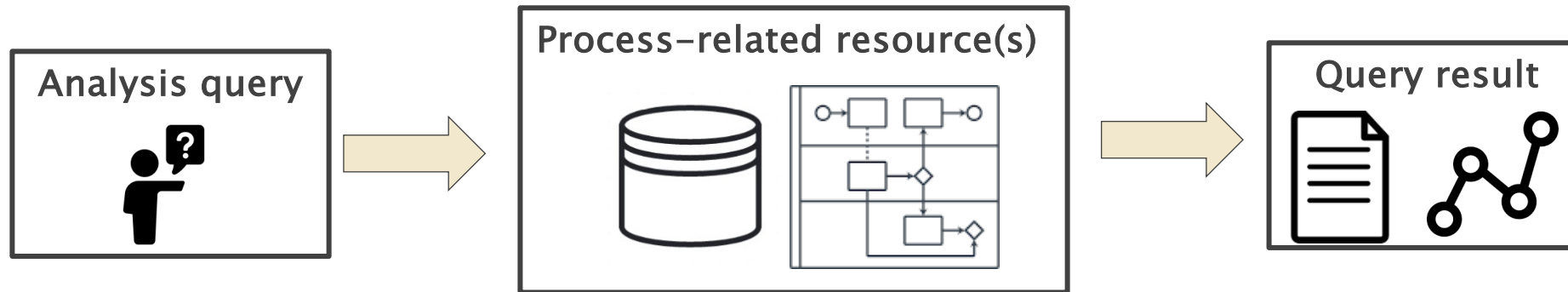
Various works exist that **allow users to provide analysis queries in a textual format**, which are then parsed and applied on an event log or process model



Examples include:

- Chatbots for process (model) comprehension (Lopez et al. 2019)
- A natural language querying interface for process mining (Barbieri et al., 2020)
- Process performance analysis using textual descriptions (Resinas et al., BPM 2023)
- C-4PM: a conversational agent for declarative process mining (Fontenla-Seco et al. BPM demo 2023)
- Chat support in pm4py (Berti et al., NLP4BPM 2023)

CASE 1: NLP AS AN INTERFACE FOR PROCESS ANALYSIS – HOW IT WORKS



Query: “[What is] the average time until a received request is reimbursed?”

Either explicitly or implicitly, using NLP as an interface requires two parts:

1. Interpreting the textual query, i.e., recognizing what the user is asking for
 - **Example:** The user wants to measure the performance of a process, specifically looking for a measure of the time between *receiving a request* and *reimbursement*, of which the case-based average should be taken.
2. Relating the parts of the interpreted query to the contents of the available process information.
 - **Example:** *receive a request* corresponds to a “*receive request*” event class, whereas *reimbursement* corresponds to a “*payment handled*” event class

CASE 2: NLP FOR PROCESS INFORMATION EXTRACTION

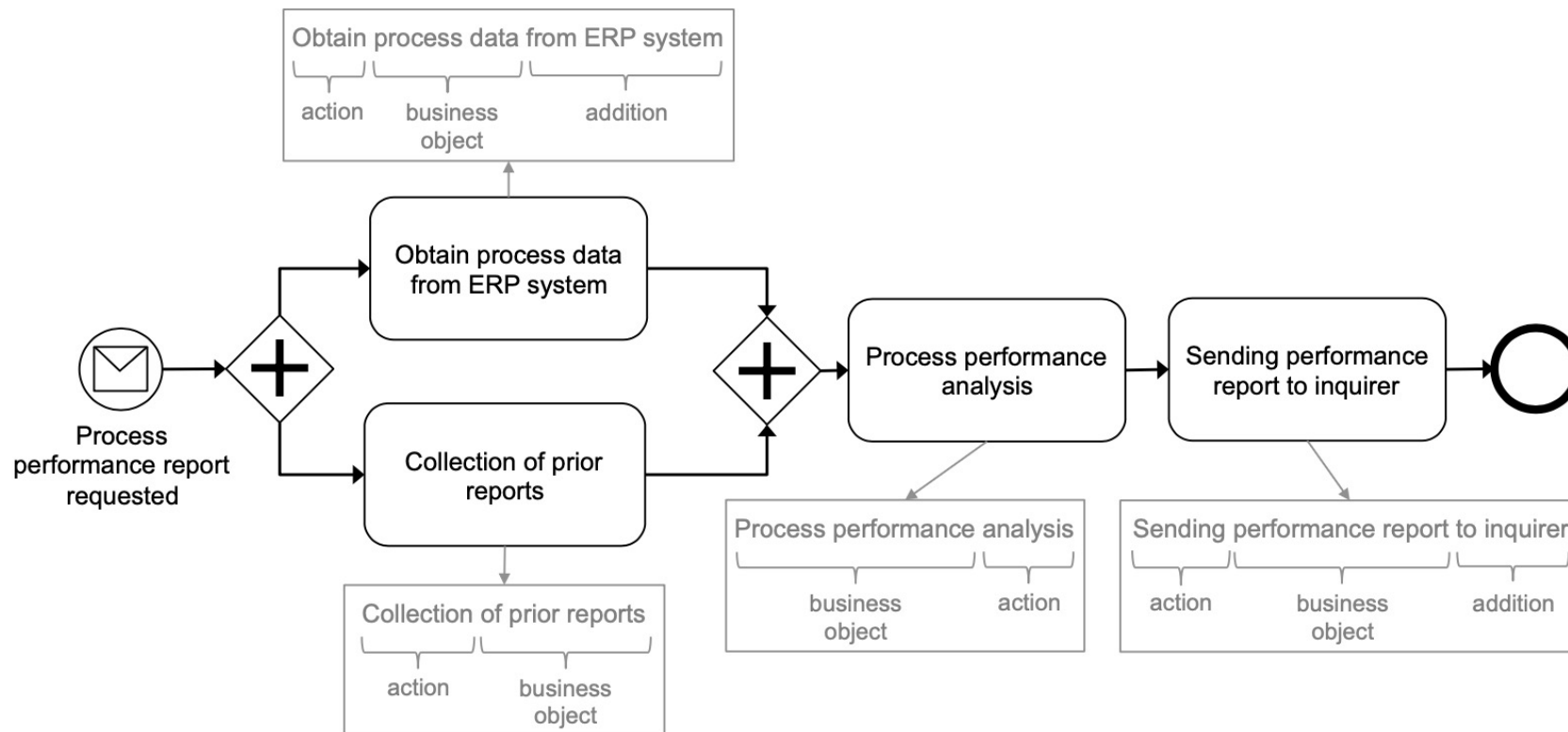
Various works focus on the extraction of process information from different resources, so that information can be used for downstream analysis tasks

Two main categories:

- Information extraction from the **textual contents of process models and event logs**. Focus here is on **uncovering semantic information** about a process, typically contained in the textual labels of activities/events, e.g., which objects and actions are involved in a process?
- Information extraction from **textual documents**, such as textual process descriptions, compliance documents, work instruction. Focus here is on deriving process information from resources that do not have an explicit process structure

CASE 2: EXTRACTING INFORMATION FROM ACTIVITY LABELS

One of the first NLP-related tasks in the BPM field focuses on the extraction of semantic information from activity labels in process models (and later event labels)



Various benefits of extracting this information:

- **Detect/correct labeling-style** issues and modeling anti-patterns within a model
- **Ensure consistency** across models
- Support **process (model) querying**
- Support **process abstraction**
- etc.

CASE 2: EXTRACTING INFORMATION FROM ACTIVITY LABELS – A HISTORY LESSON

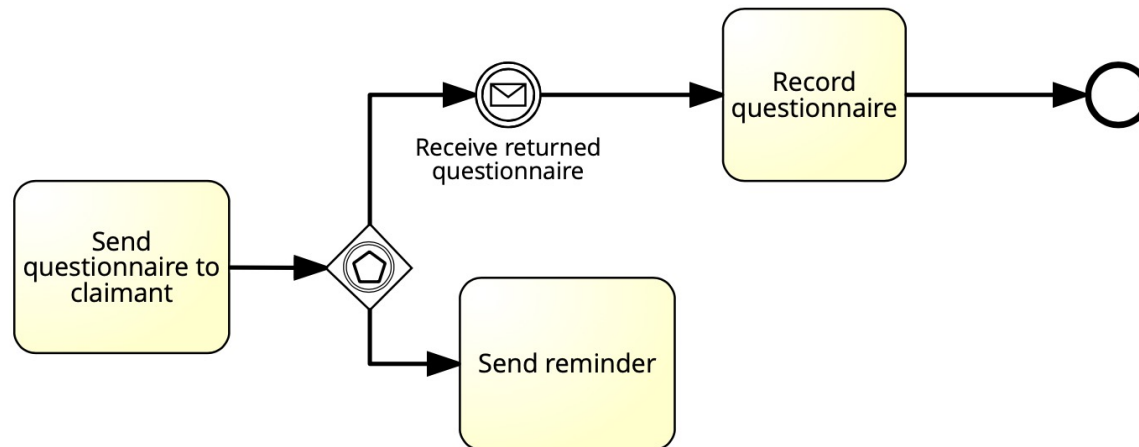
1. First approaches **used rule-based algorithms** to detect semantic components in specific labeling styles, mainly verb-object (*create offer*, *measure distance*) and action-noun (*offer creation*, *distance measurement*) (cf., Leopold et al., 2012)
 - Such approaches were necessary because general-purpose NLP techniques were not able to properly extract information from short textual snippets.
 - **Lots of work for comparatively little:** limited generalization, just two labeling styles, just focusing on actions and objects
2. Next, approaches **using machine learning**, training e.g., hidden markov models, on annotated collections of labels (Leopold et al., 2019)
 - **Reduced the involved effort**, especially easier to branch out to different labeling styles, yet can deal poorly (or not at all) with new styles
3. Then, started to use fine-tuned language models (e.g., BERT) for this task (Rebmann and vd Aa, 2021)
 - **Improved the generalization capabilities**, since not just trained on process data anymore, but also using general language training. **Great for event labels**, which can have wildly different informational contents (e.g., *Declaration final_approved by supervisor*). Also extract more **information components**
4. Now, **the age of generative (and extra large) language models**, which essentially allows you to extract information from labels in a zero-shot manner, using the right prompt
 - **Highly powerful, easy to use, no need for a specific model** for just this task. In some edge cases, fine-tuned models may work better, plus models may have high costs

CASE 2: EXTRACTING PROCESS INFORMATION FROM TEXTUAL DESCRIPTIONS

Key task to extract information, often, ultimately with **the goal of turning the described process into a process model** or otherwise structured representation (e.g., compliance rules, DMN)

The customer office sends the questionnaire to the claimant by email.
If the questionnaire is received, the office records the questionnaire and the process end.
Otherwise, a reminder is sent to the customer.

(Bellan et al., 2022)



Technique development generally follows the same pattern as label parsing

But, **process model extraction from text is highly challenging:**

- Often ambiguity in descriptions
- Texts can use very different styles, also contents may not all relate to a process description
- Long-distance dependencies between different process branches
- Little training data available

CASE 3: SEMANTICS/TEXT-AWARE PROCESS ANALYSIS

Finally, there are a variety of works that use textual information (either extracted or not) within process analysis techniques itself:

- Text-aware process prediction (Brennig et al., NLP4BPM'23)
- Role recognition & process abstraction (Rebmann, vd Aa, IS'21)
- Semantic anomaly detection (Van der Aa et al., IS'21, Berti et al., NLP4BPM'23, Caspary et al., BPM'23)

But there may be much **more coming in the future**, particularly interesting to see if NLP-based techniques can be actually used for **process improvement, rather than just analysis**

Interested in that?

- Time-machine back to yesterday's NLP4BPM round table (tricky..)
- Check out the workshop's papers by Berti et al. and Jessen et al. who started doing early experiments on this

Trace 2	
A	Create order
B	Check order
C	Approve order
D	Reject order
F	Complete delivery



PART 3: HANDS-ON SESSION

HANDS-ON SESSION: OVERVIEW

- Python notebook with hands-on exercises on NLP for BPA
- Focus on using LLMs for process analysis:
 - 1. Event log analysis
 - 1.1 Importing and analyzing an event log with LLMs and pm4py
 - 1.2 Creating functions for custom tasks: action and object extraction from event labels
 - 1.3 Label standardization
 - 1.4 Action type categorization
 - 2. Analyzing textual process descriptions: Imperative model extraction from text
 - 3. Future of NLP for BPA
- If you want to follow along, please use this link to get to the notebook: <https://tinyurl.com/nlp4bpa>
- We run the notebook in Google Colab (link is provided in the notebook), which requires a Google account

Q&A

REFERENCES IN PRESENTATION

- López, A., Sánchez-Ferreres, J., Carmona, J., & Padró, L. (2019). From process models to chatbots. In Advanced Information Systems Engineering: 31st International Conference, CAiSE 2019, Rome, Italy, June 3-7, 2019, Proceedings 31 (pp. 383-398). Springer International Publishing.
- Barbieri, L., Madeira, E., Stroeh, K., & van der Aalst, W. (2022). A natural language querying interface for process mining. *Journal of Intelligent Information Systems*, 1-30.
- Resinas, M., del-Río-Ortega, A., & van der Aa, H. (2023). From Text to Performance Measurement: Automatically Computing Process Performance Using Textual Descriptions and Event Logs. In *International Conference on Business Process Management* (pp. 266-283). Cham: Springer Nature Switzerland.
- Yago Fontenla-Seco, Sarah Winkler, Alessandro Gianola, Marco Montali, Manuel Lama Penin and Alberto Bugarín-Diz (2023). The Droid You're Looking For: C-4PM, a Conversational Agent for Declarative Process Mining. BPM Demo track
- Alessandro Berti, Daniel Schuster, and Wil M. P. van der Aalst (2023). Abstractions, Scenarios, and Prompt Definitions for Process Mining with LLMs: A Case Study. NLP4BPM workshop
- Henrik Leopold, Sergey Smirnov, Jan Mendling: On the Refactoring of Activity Labels in Business Process Models. *Information Systems* 37(5): 443-459, 2012.
- Henrik Leopold, Han van der Aa, Jelmer Offenberg, Hajo A. Reijers: Using Hidden Markov Models for the Accurate Linguistic Analysis of Process Model Activity Labels. *Information Systems* 83: 30-39, 2019.
- Adrian Rebmann, Han van der Aa. Enabling Semantics-aware Process Mining through the Automatic Annotation of Event Logs. *Information Systems*, 110: 102111, 2022
- Patrizio Bellan, Han van der Aa, Mauro Dragoni, Chiara Ghidini, Simone Paolo Ponzetto. PET: An Annotated Dataset for Process Extraction from Natural Language Text Tasks. 1st Workshop on Natural Language Processing for Business Process Management (NLP4BPM 2022)
- Katharina Brenning, Kay Benkert, Bernd Löhr, and Oliver Müller. Text-Aware Predictive Process Monitoring of Knowledge-Intensive Processes: Does Control Flow Matter? (NLP4BPM 2023)
- Urszula Jessen, Michal Sroka, and Dirk Fahland. Chit-Chat or Deep Talk: Prompt Engineering for Process Mining (short paper) (NLP4BPM 2023)
- Julian Caspary, Adrian Rebmann, Han van der Aa. Does This Make Sense? Machine Learning-based Detection of Semantic Anomalies in Business Processes. *International Conference on Business Process Management (BPM 2023)*

COMPLEMENTARY TUTORIAL (THURSDAY 14:00 – 15:30)

Tutorial 3: Using Large Language Models in Business Processes

Thomas Grisold, Jan vom Brocke, Wolfgang Kratsch, Jan Mendling, and Maxim Vidgof

Large language models, such as ChatGPT, provide ample opportunities for organizational work. These models are capable of collecting, integrating, and generating information with no or little human supervision. Despite their wide and rapid uptake, we lack systematic knowledge about how large language models can be used in business processes.

Our tutorial sheds light on the organizational, managerial and design-related implications of using large language models in business processes.

- We **present a theoretical framework** that integrates and synthesizes research from relevant streams, including task complexity, task automation, and human-AI delegation.
- We **specify potential opportunities and threats** in relation to various forms of tasks, such as decision tasks and judgment tasks.
- Along these lines, we also **explore how the use of large language models may affect the overall outcome of a process**, for example, by providing new value propositions.
- We use, reflect, and discuss the implications of our framework based on real-world examples. Our conceptual framework is relevant to guide future research but also inform managerial decisions in organizations.

THANK YOU!