Natural Language Generation from Process Models

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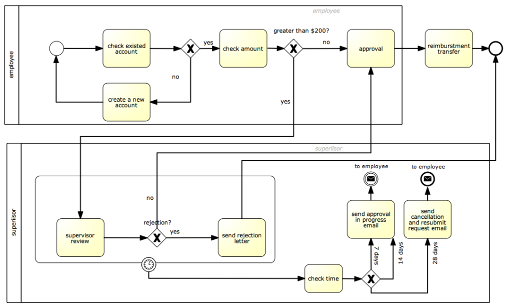
Motivation: Domain Expert and Model

Domain Expert

Reads



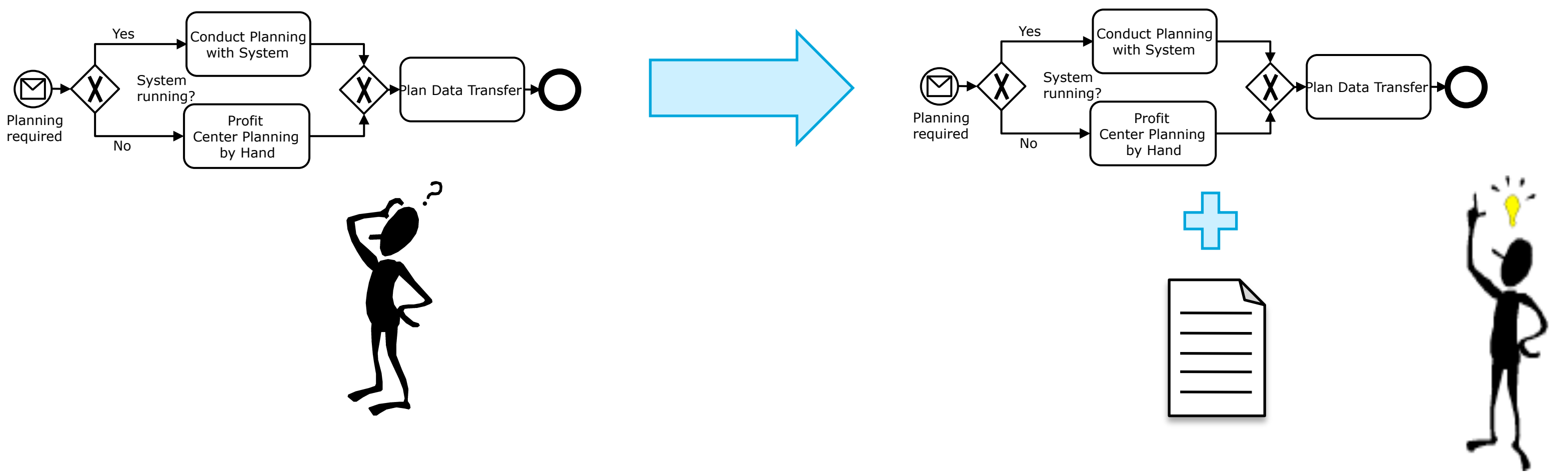
Process Model

Understands?

Represents

Research goal

Goal: Automatically generate natural language texts from business process models.



How can we generate Texts?

Natural Language Generation approaches can be divided into two main classes:

- **Canned text / Template filling approaches**
  - Direct mapping of input to output text
  - Example: In the <*min*> minute a goal was scored by <*player*>.
- **“Real” NLG Systems**
  - Use intermediate data representations
  - Require linguistic knowledge / tools

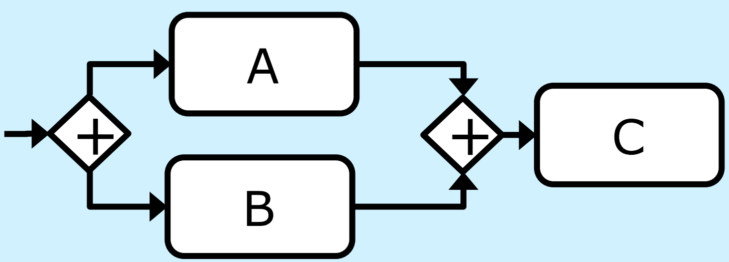
Challenges (1/2)

1. Text Extraction

Plan Data Transfer

Role: analyst
Action: transfer
BO: plan data

2. Text Planning



… A, B, C …

Challenges (2/2)

3. Message Generation

Role: analyst
Action: plan
BO: measure

Role: analyst
Action: prepare
BO: measure

⇨

Role: analyst
Action: plan, prepare
BO: measure

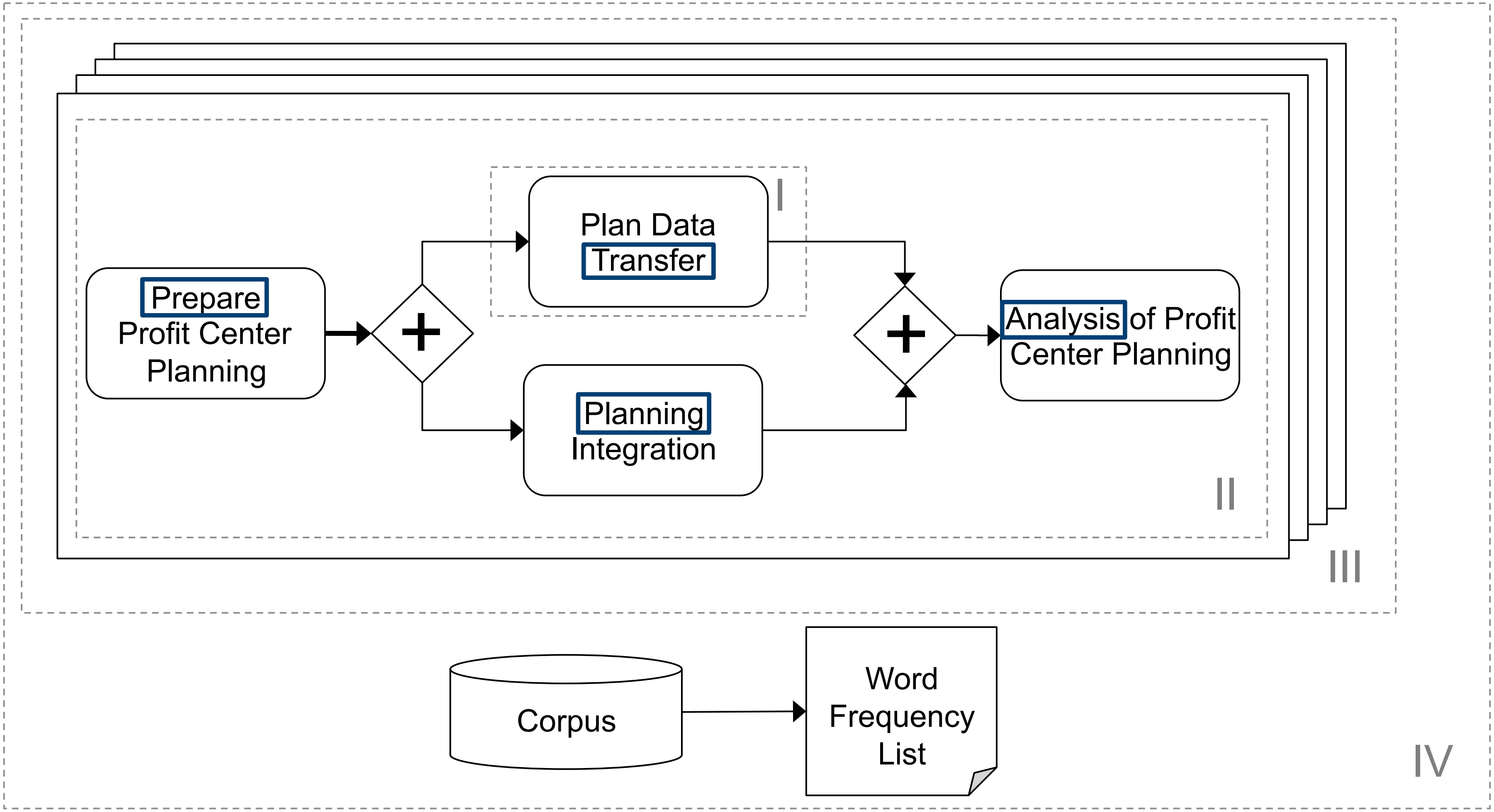
4. Surface Realization

Role: analyst
Action: plan, prepare
BO: measure

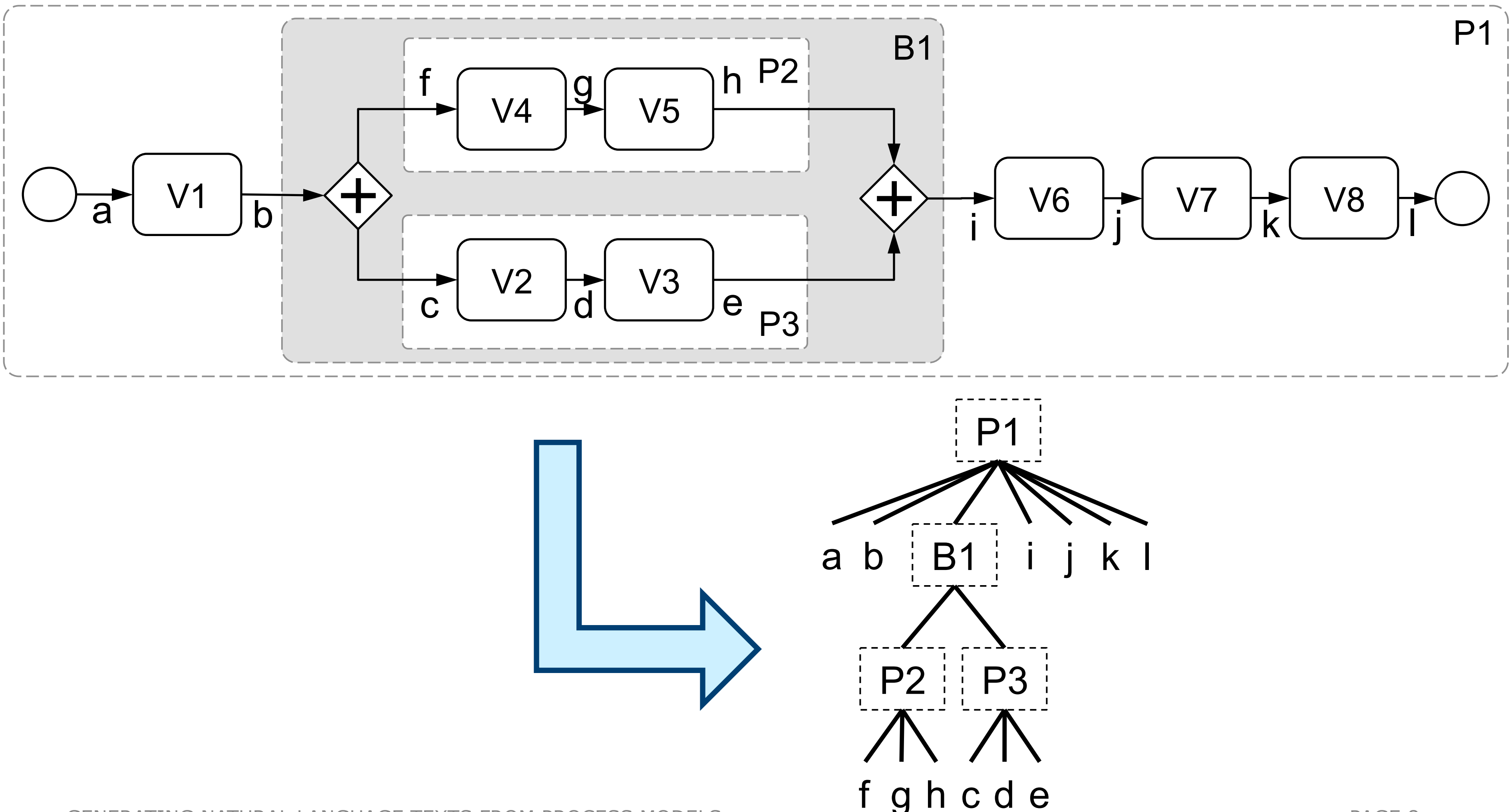
⇨

The analyst plans and prepares the measure.

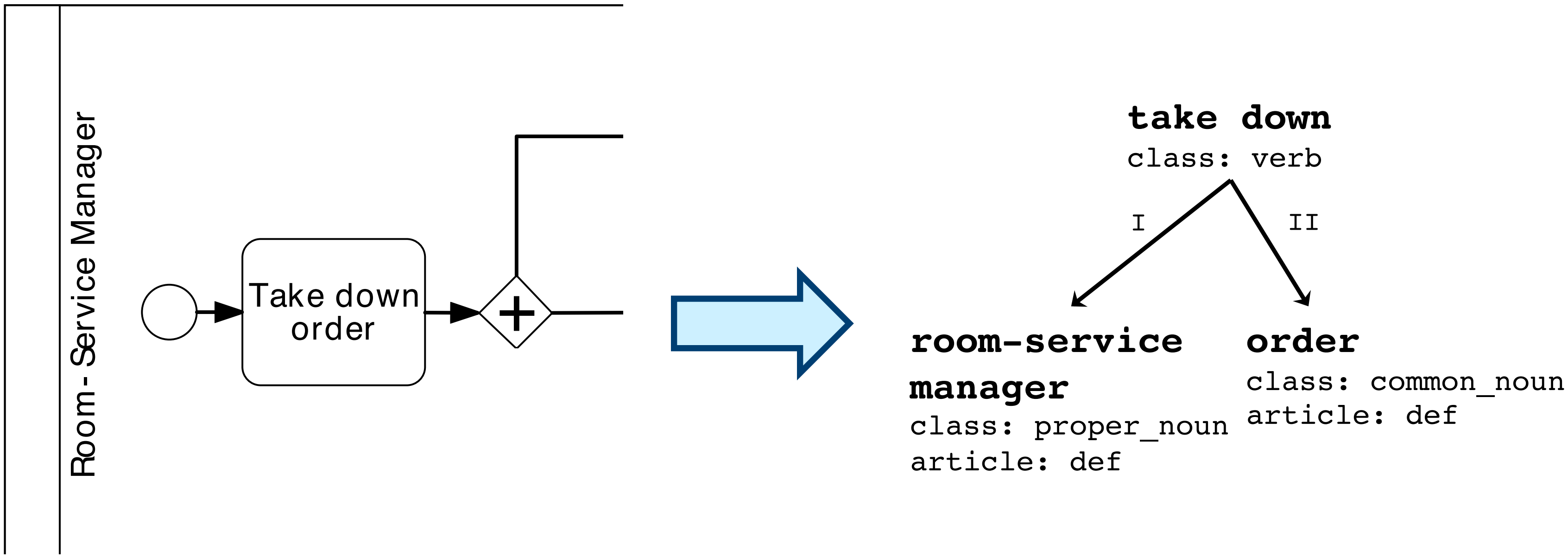
1. Linguistic Information Extraction



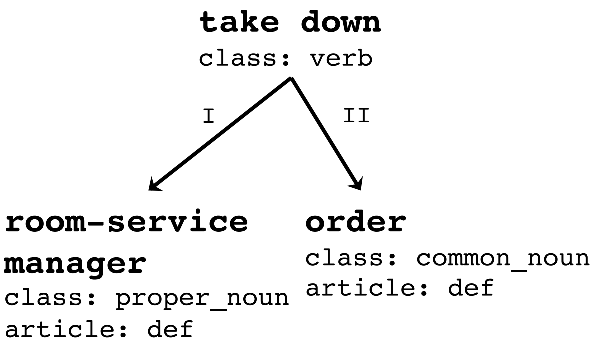
2. Text Organization

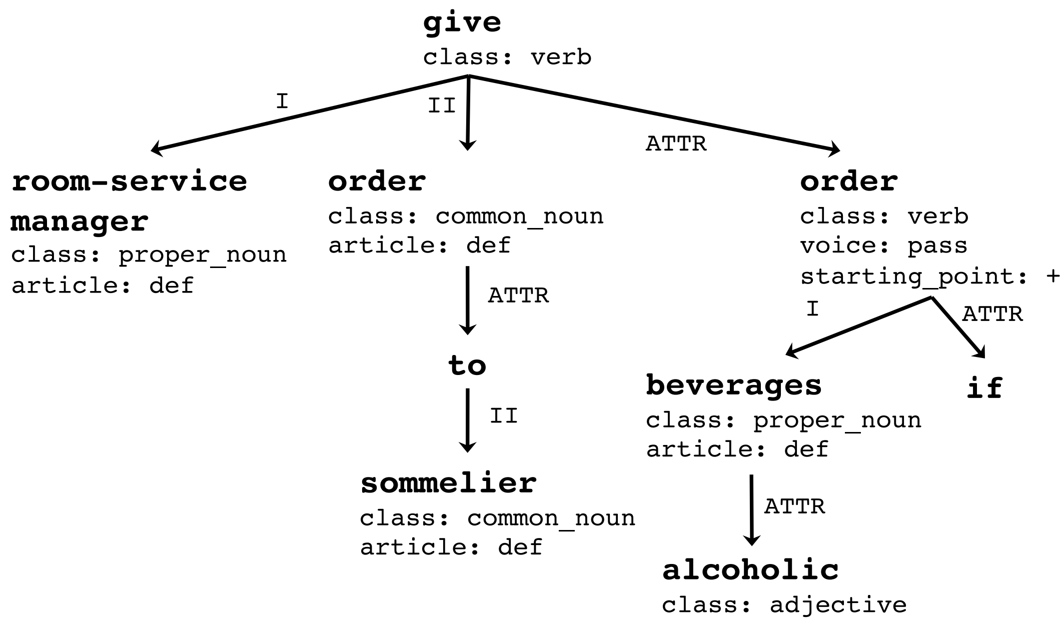


3. Message Generation



4. Linguistic Realization

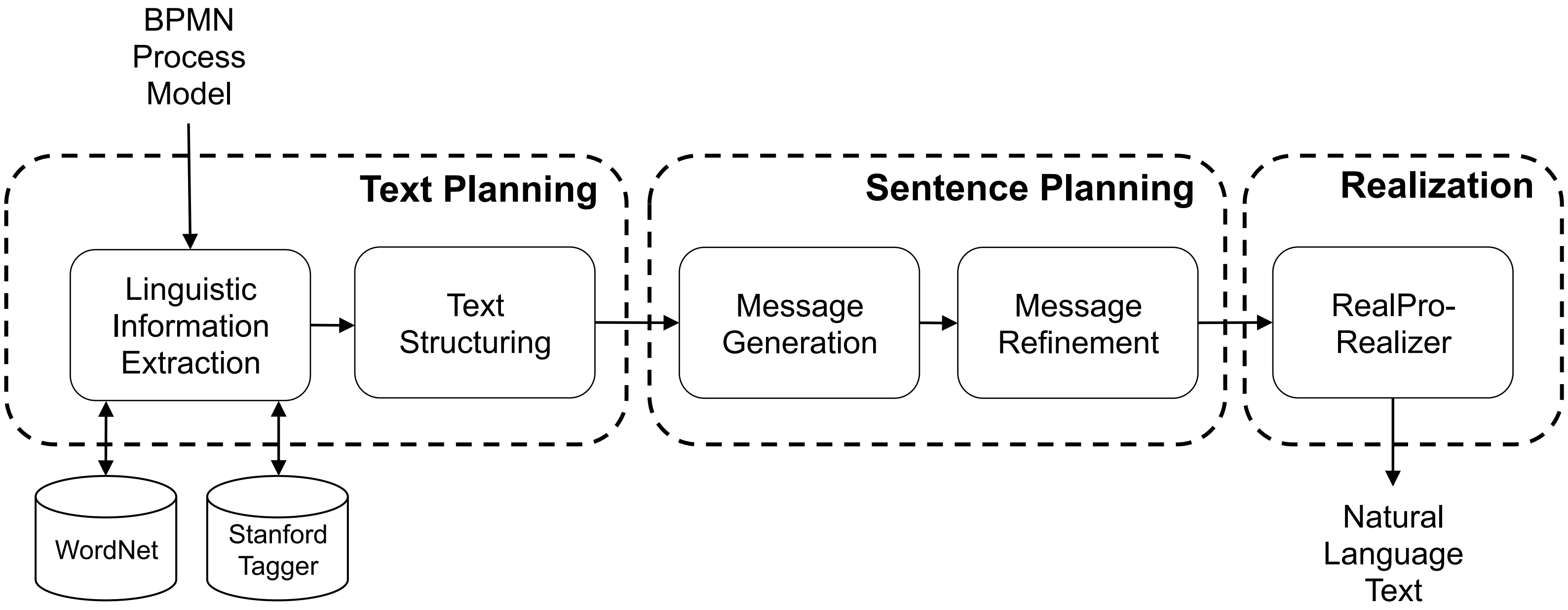




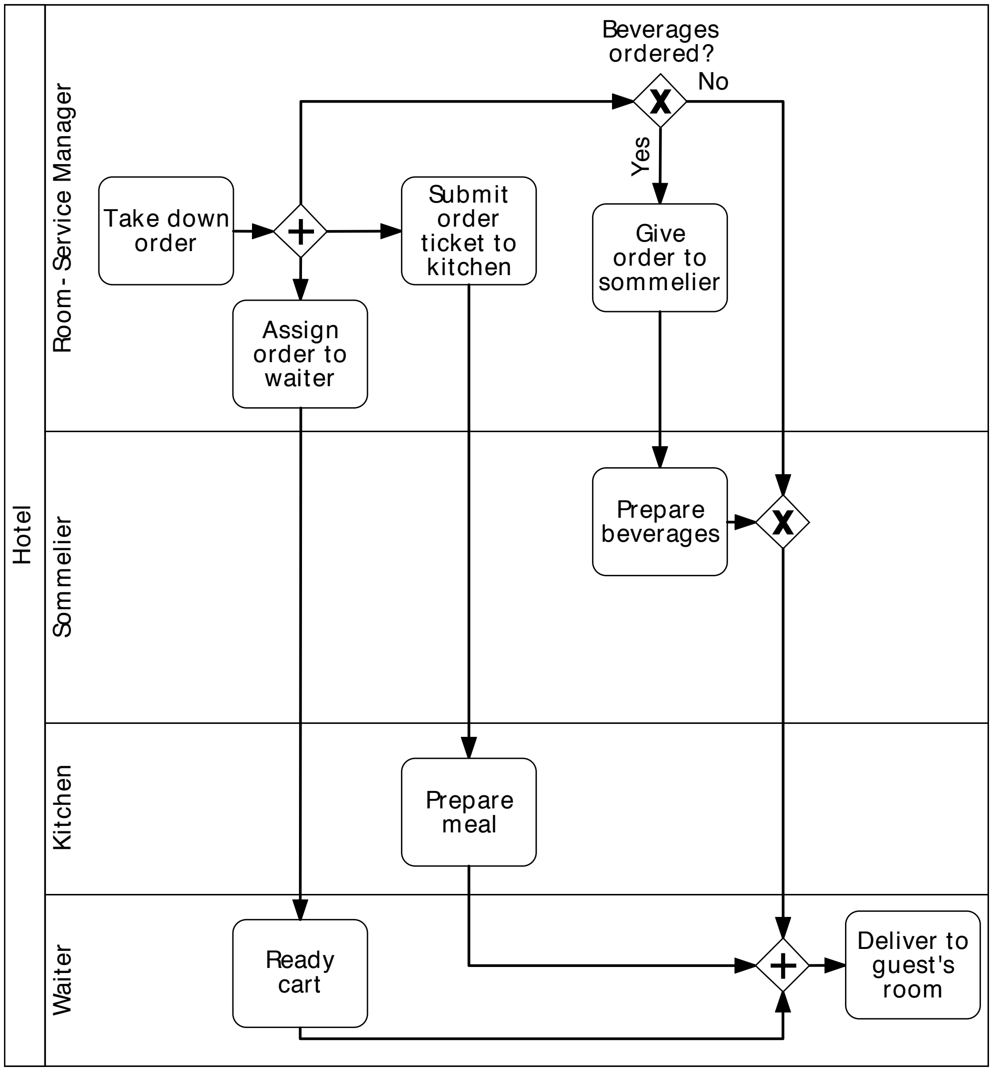
"The room-service manager takes down the order."

„If alcoholic beverages are ordered,the room-service manager gives the order to the sommelier.“

Architecture of the NLG System



Example of Generated Text



The process begins when the Room-Service Manager takes down an order. Then, the process is split into 3 parallel branches:

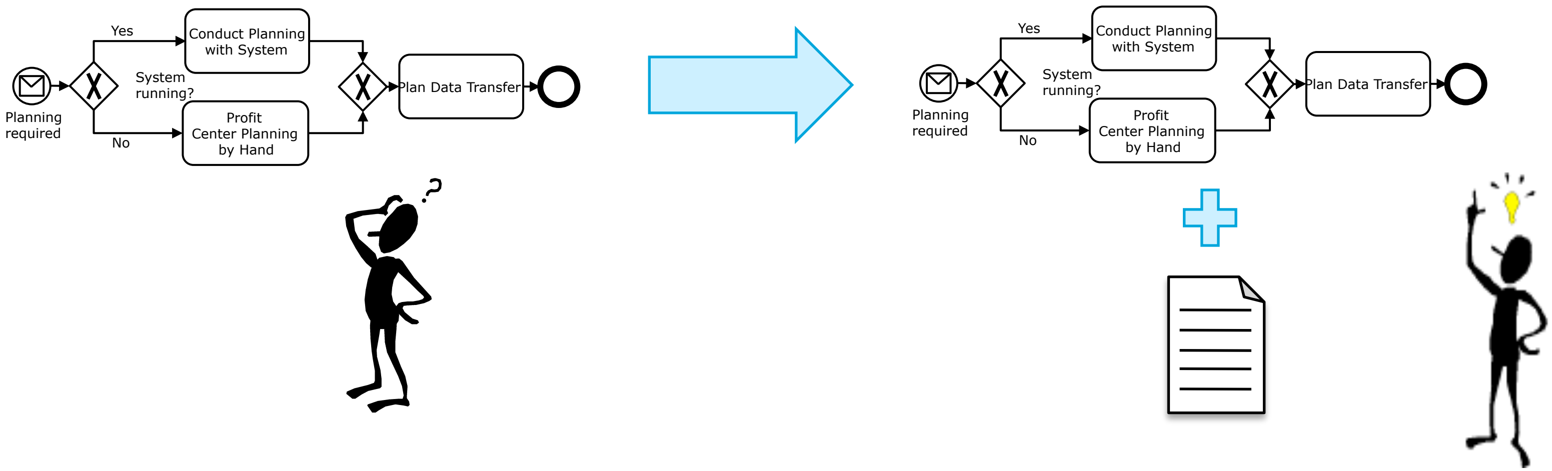
- In case beverages are ordered, the Room-Service Manager gives the order to the sommelier. Afterwards, the Sommelier prepares the beverages.
- The Room-Service Manager assigns the order to the waiter. Subsequently, the Waiter readies the cart.
- The Room-Service Manager submits the order ticket to the kitchen. Then,the Kitchen prepares the meal.

Once all 3 branches were executed, the Waiter delivers to the guest's room and the process is finished.

Evaluation

- Idea: Back translation experiment with users
- We asked 11 users to transform 3 generated texts back into process models
- We selected texts representing models of varying complexity (from 6 to 26 activities)
- From 33 models, 22 perfectly matched their original
- Lowest similarity score was 83%

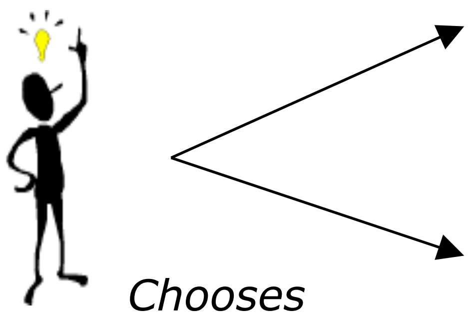
Follow-up experiment



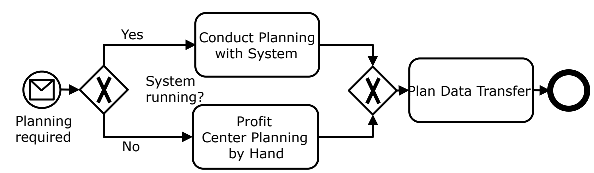
Do the generated texts actually achieve this goal?

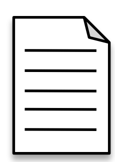
What Theory says about Model versus Text (1/3)

- **Learning Preference Hypothesis**: “It is possible and desirable to adapt the nature of instruction to accommodate differences in the ability, style, or preferences among individuals to improve learning outcomes” (Jonassen & Grabowski, 1993)



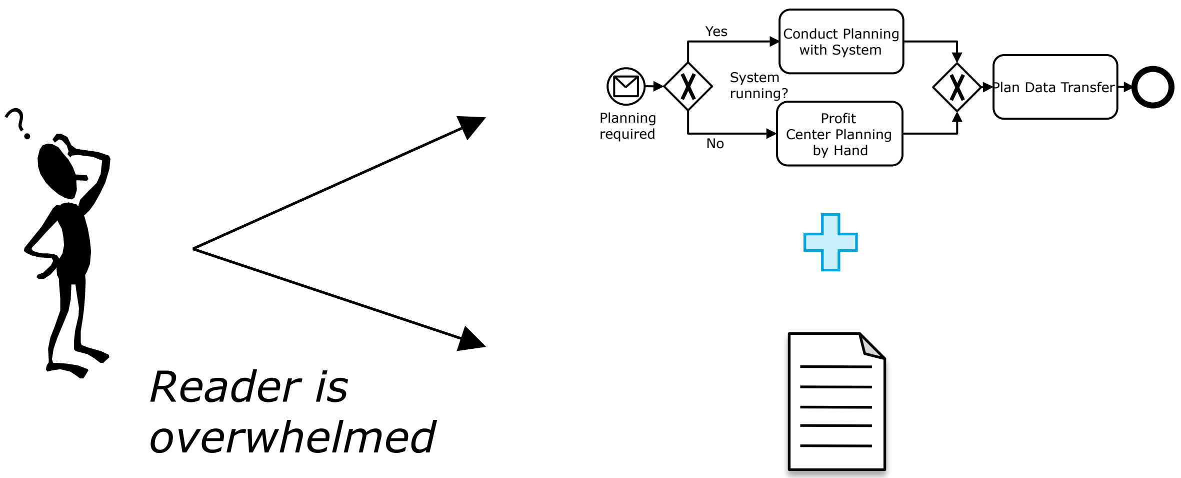
Chooses preferred representation





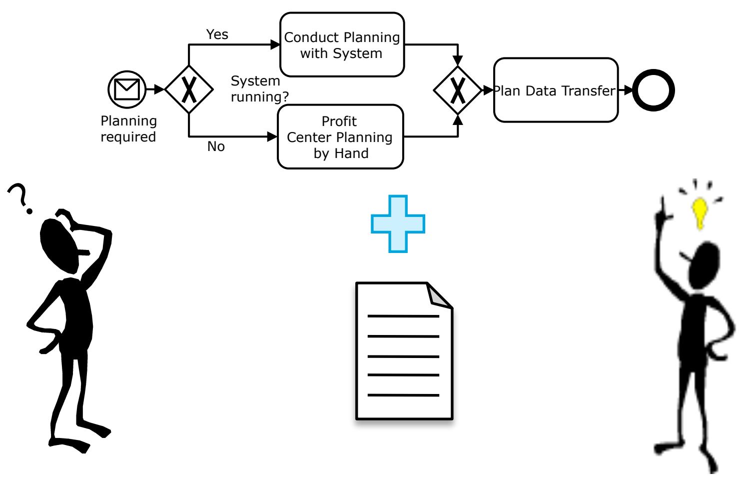
What Theory says about Model versus Text (2/3)

- **Redundancy Principle & Capacity Limitation Hypothesis**: Text and model must be processed by the learner and incorporated into the learning memory. It is better to omit one of them. (CTML, Mayer 2008)



What Theory says about Model versus Text (3/3)

- Cognitive Theory provides contradicting viewpoints
- We decided to conduct an experiment to demonstrate whether a natural language text can improve model understanding

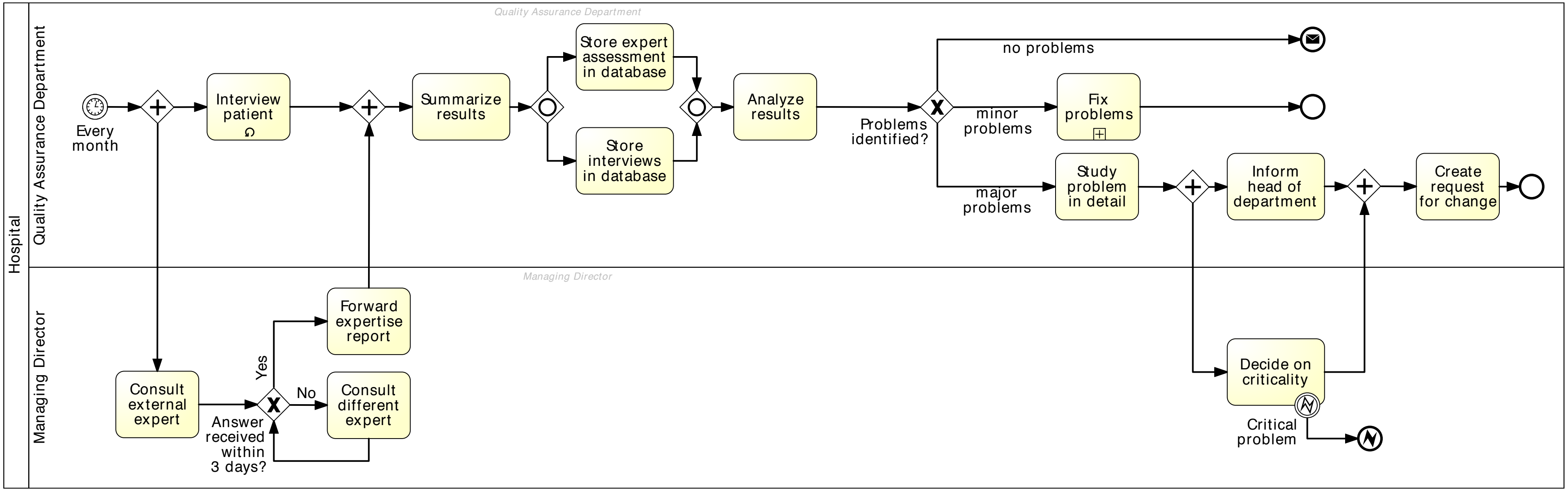


Design of an Experiment on the Effect of a Complementary Text

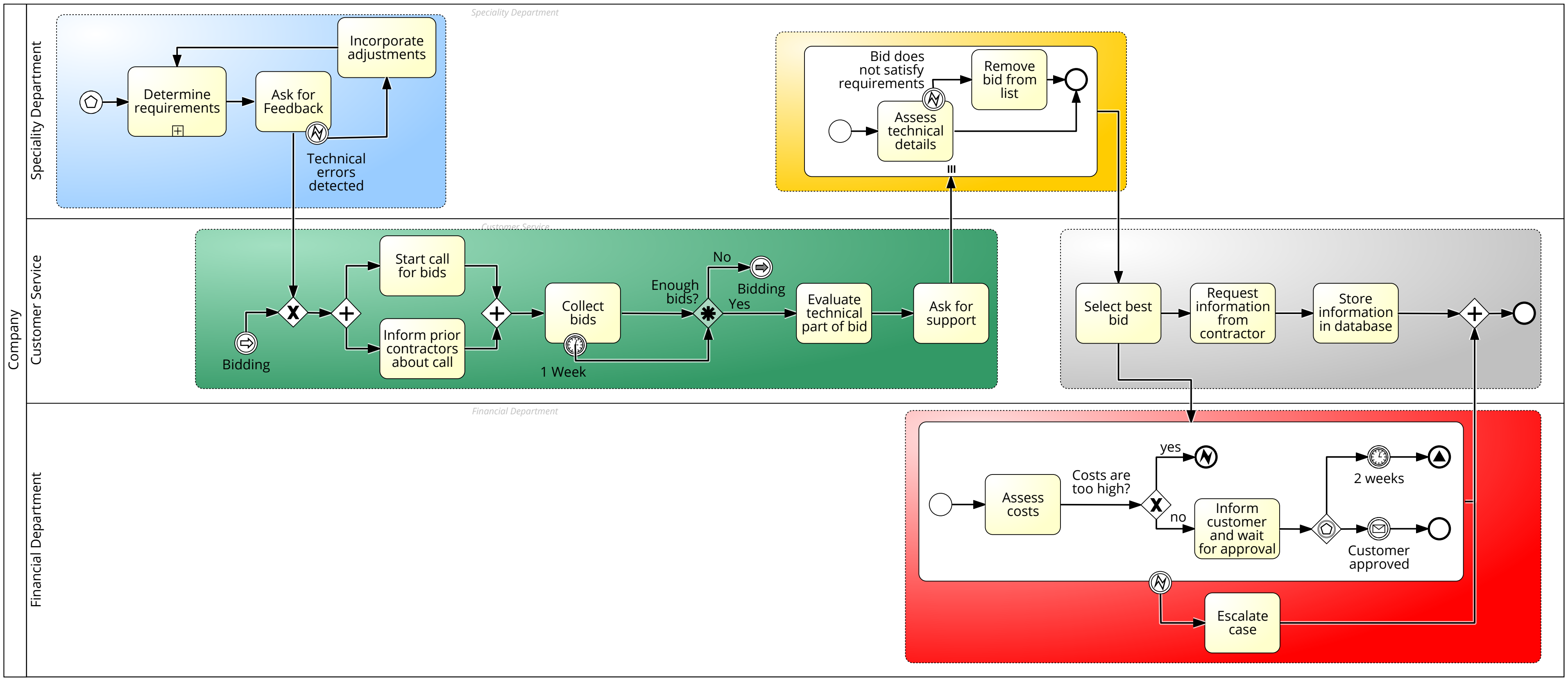
- We considered three factors:
  1. Natural Language Text (between-subject, yes/no)
  2. Complexity of process model (within-subject, average/high)
  3. Color Segmentation (within-subject, yes/no)
- Each participant received 4 process models:

	Factor	**M1**	**M2**	**M1'**	**M2'**
Group A	Text	Yes	Yes	Yes	Yes
	Complexity	Avg.	High	Avg.	High
	Color	No	No	Yes	Yes
Group B	Text	No	No	No	No
	Complexity	Avg.	High	Avg.	High
	Color	No	No	Yes	Yes

Design of an Experiment on the Effect of a Complementary Text



Design of an Experiment on the Effect of a Complementary Text



Design of an Experiment on the Effect of a Complementary Text

- Task of participants was to answer 10 questions for each model
- Three choices for each question
- Questions cover aspects related to symbols as well as behavior
- We use the responses to calculate:

1. Comprehension accuracy (sum of correct answers)
2. Comprehension efficiency (accuracy / time)

Participants

- We recruited 159 students from the TU Eindhoven with mixed background

Variable	**Group A**	**Group B**
n	94	65
Age	23.5	22.9
Gender (f / m)	26% / 74%	30% / 70%
No. of BPM courses	2.9	3.1
Familiarity with BPMN	4.28	3.89
Competence for using BPMN	3.99	3.65

Preliminary Results

- Group A obtains higher scores for all 4 models (significant at 0.01 level)
  - M1: 7.85 vs. 6.82
  - M2: 6.67 vs. 5.63
  - M1’: 8.03 vs. 7.28
  - M2’: 6.32 vs. 5.57
- Group A also has a better comprehension efficiency (significant at 0.01/0.05 level)
- No clear effect for color segmentation
- No clear effect of complexity

Summary

- We successfully generated natural language texts from process models
- Evaluation shows that generated texts are equivalent in terms of content
- Experiment with 159 students shows the positive effect of natural language texts on model understanding

Henrik Leopold, Jan Mendling, Artem Polyvyanyy: **Supporting Process Model Validation through Natural Language Generation**. IEEE Transactions on Software Engineering 40(8): 818-840, 2014.


Questions?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