A Language Models

 Language models have revolutionized the field of natural language processing thanks to recent advancements in model design³⁵, along with a wide availability of text datasets ³⁶ and capacity to scale to large computational budgets. These models are generally trained to predict the likelihood of tokens in text sequences. The most successful models in the field, the Transformers , employ an attention mechanism³⁷ to weigh the importance of each word in a sentence when predicting the next word, thereby learning to extract long-rage dependencies from text sequences.

 Two relevant pretrained models are GPT-4²⁷ and Flan-T5²⁸. These state-of-the-art models have been built and trained for different purposes, and thus serve different purposes.

A.1 GPT-4

 GPT-4 is a decoder-only model developed by OpenAI²⁷ trained with an autoregressive objective on large text datasets to generate human text. Capabilities of this, and similar models, include translation, question-answering and general content creation, however additional capabilities have been demonstrated such as chain-of-though reasoning²⁹, in-context learning¹⁸, and capacity to use \cdot tools 38 .

 In combination, these capabilities make it possible for users to solve generic NLP problems by simply prompting the model with explanations about how to complete the task, along with examples and

other relevant information.

A.2 FLAN-T5

 FLAN-T5 is a model developed by Google²⁸ whose training paradigm is that any NLP problem is a text-to-text problem. Under this setting, instead of training individual models for each task, T5 unifies a number of tasks into a single framework as a text generation task.

 For our purposes, a key property of the FLAN-T5 model is that it can be fine-tuned to perform any text-to-text task, for which enough data is available, which yields a model with a small parameter count, facilitating local inference and escalation to large datasets. GPT-4, on the other hand, can only be accessed through a costly API, that is additionally restricted to one API call per generation, preventing batches of data to be processed.

B Semantic segmentation model

 As discussed, the analysis centers initially in decomposing synthesis procedure paragraphs into semantically distinct segments belonging to different classes, namely "reaction set-up", "work-up", "purification" and "analysis". An example of a solution to this task is given in Figure [3.](#page-1-0) Solving this task requires that the model learns to copy and paste text from the input, into the output, however separating the different segments based on their meaning in the context of a chemical synthesis, while also assigning a label or class to each.

 The task cannot be trivially formulated as a per-sentence classification task as, as shown in Figure [3,](#page-1-0) some segments can actually extend up to the first words of the next sentence and beyond, as is the case of the piece "Stir for 30 hours,", which belongs together with the "reaction set-up" segment. The semantic segmentation task thus requires certain level of contextual understanding, making (large) language models suitable candidates for solving the task.

B.1 Knowledge Distillation

 Knowledge distillation is the process where the knowledge from a more capable model is *distilled* to be transfered to another, potentially cheaper model 39 . In the case of the paragraph segmentation task, we found that LLMs like GPT-3.5 and GPT-4 excelled when adequately prompted, thanks to their demonstrated abilities to follow instructions and formats, and produce step-by-step reasoning sequences. The following text was used as a template prompt to achieve the desired behavior from the models:

Input paragraph:

```
{
    'text segment': 'Suspend anhydrous AlCl3 (156 g, 1.15 mol) in toluene (1500 mL) 
 and cool to 2-4° C. Add, by slow addition, a solution of 4-chlorobutyryl chloride 
 (165.5 g, 1.15 mol) in toluene (300 mL). Stir for 15 minutes and pour into stirring 
 ice-water (2.5 L). Stir for 30 hours,,
      'text class': 'reaction set-up',
      'step order': 1,
 }
 {
     'text segment': 'decant the toluene and extract the aqueous phase with toluene 
 (700 mL). Combine the organic layers and wash three times with water (1 L, 1 L, 
 500 mL).',
     'text class': 'work-up',
     'step order': 2
 },
   {
     'txt_sgm': 'Evaporate the solvent in vacuo to give the title compound as a pale 
 yellow oil (292.3 g, 95%).',
     'segment class': 'purification',
     'step order': 3
 }
 Suspend anhydrous AlCl3 (156 g, 1.15 mol) in toluene (1500 mL) and cool to 2-4° C. 
 Add, by slow addition, a solution of 4-chlorobutyryl chloride (165.5 g, 1.15 mol) in 
 toluene (300 mL). Stir for 15 minutes and pour into stirring ice-water (2.5 L). Stir for 
 30 hours, decant the toluene and extract the aqueous phase with toluene (700 mL). 
 Combine the organic layers and wash three times with water (1 L, 1 L, 500 mL). 
 Evaporate the solvent in vacuo to give the title compound as a pale yellow oil (292.3 
 g, 95%).
Output segmentation:
```
Figure 3: Example of the semantic segmentation task for synthetic procedure paragraphs. The color code shows the origin of each extracted segment from the original paragraph.

371 The placeholder *example* is replaced by the text below, that gives an idea to the LLM of what the output should look like.

B.2 Model training

 Nearly 30k samples were obtained from GPT-4 and GPT-3.5 using the prompt above. To transfer this task to a smaller specialist model, we fine-tuned a **flan-t5-large** model using the adapters⁴⁰ library.

 To fully profit from the generated dataset, a 2-stage training procedure was followed, where at first the model is fine-tuned on the more abundant –however potentially less accurate– GPT-3.5 dataset in order for it to learn the format and an initial representation of what the task is about. The model is subsequently fine-tuned on the GPT-4 dataset, which is more scarse but assumed to be better quality.

 For every stage of training a batch size of 2 was used, over 20 epochs, with a linear learning rate decay starting from 5e-4.

B.3 Output post-processing

 Although the resulting model behaves well in multiple situations, in some cases it can generate erroneous outputs by copying the same sentence multiple times, or by missing some text in the output. These cases can easily be detected by calculating the edit distance between the original paragraph and the concatenation of all the output segments which, if correctly done, should equal zero.

 With this, we found that the resulting model produces output with satisfactory results in around 66% of cases. This filtering technique is further extended to the inference step to the whole USPTO database, to ensure data quality.

C Segment Embedding Maps

 To explore the rich structure of the newly defined semantic subspaces, the sentence embeddings for each segment were calculated and plotted using different labels, in order to facilitate pattern- finding. Yield was chosen as it was readily available as a part of the dataset; the resulting plots are shown in Figure [4.](#page-6-0) As can be seen, despite the rich structure observed in each space, there is very little correlation with yield. Although some localization of colors can be seen in e.g. work-up and purification, it must be noted that these two types of segments typically contain the yield textually, so the patterns shown may be an artifact. Still, as previously noted by other authors, yield prediction is a s_{21} very challenging issue^{41–44}, due to the noisy nature of data⁴⁵ and other social factors such as lack of 522 overlap of different research works⁴¹.

 Inspection of the purification and analysis plots (Figure [4c](#page-6-0),d) shows even more structure than the other two, however these are less interesting as clustering in this case is correlated with clearly defined concepts in each subspace, such as different types of purification, or the multiple analytical techniques. A more in-depth exploration of these spaces would be required to discover new insights, such as for instance clusterings by type of products in the analysis space, which would make sense knowing that results from analytical chemistry typically encode structural information about the analysed susbtances.

Figure 4: UMAP of each of the defined semantic subspaces, as colored by reaction yield.